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The Persuasive Power of Instagram Metrics: Examining How User-Generated Cues Affect Consumer's Perception of Influencer Credibility

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THESIS

A thesis submitted in partial fulfillment of the
requirements for the degree of Master of Arts in the
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at the University of Kentucky

By

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ABSTRACT OF THESIS

The Persuasive Power of Instagram Metrics: Examining How User-Generated Cues Affect Consumer's Perception of Influencer Credibility

Since 2019, Instagram has been testing the removal of a visible like count on posts. This change particularly pertains to social media influencers whose popularity is visibly displayed through the number of likes and comments their posts receive. Therefore, the present study experimentally investigated how varying levels of the like (i.e. hidden, approximate, and exact) and comment (hidden and exact) display on Instagram's Explore page affect user's credibility evaluations of unknown influencers. Guided by the Heuristic Systematic Model, MAIN Model and Warranting Principle, this study conducted a 3 (like display: hidden likes, approximated number of likes, and exact number of likes) x 2 (comments display: hidden comment count and visible comment count) x 2 (influencer type: travel and food) mixed-design online experiment. Three hundred twenty-eight participants were randomly assigned to one of six conditions in which they viewed two posts in a random order, one from a fictional travel influencer and one from a fictional food influencer, and then responded to questions regarding their perceived source credibility of the influencers. The results show that the visibility of likes and comments does not significantly affect source credibility perceptions of influencers. Thus, this study offers practical implications for influencers that Instagram's removal of a visible like count will not harm their credibility. Also, this study provides suggestions for future studies to uncover what factors affect an influencer's perceived source credibility on the Explore page of Instagram.

Keywords: Instagram, Visibility of User-Generated Engagement, Credibility, Heuristic Systematic Model, MAIN Model, Warranting Principle

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DEDICATION

To *my twin Rachel, who has been with me every step of the way and unknowingly inspired my study of this research topic.*

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CHAPTER 1. INTRODUCTION

1.1 The Rise of the Instagram Influencer

Instagram launched on October 6, 2010, as a platform that would allow users to digitally connect with their friends through photos (Instagram Press, 2020a). Ten years later, Instagram has evolved to offer new features beyond photo-sharing such as Reels and Stories, and connected over a billion people across the globe (Instagram Press, 2020a). While Instagram started as a digital hub to connect with friends and family, it has evolved into a space to discover, connect, and share opinions with users from around the world. While communicating opinions were once confined to small-scale conversations between acquaintances, social media has expanded the scope of communication and ultimately the sphere of influence (Scott et al., 2011). Through an online public profile, a message of opinion from an individual can be broadcasted to anyone else within the network (Boyd & Ellison, 2008). The app has aided ordinary individuals as they rise to fame and become "instacelebrities" based on their ability to amount large quantities of followers (Frier, 2020). Ordinary consumers can grow their influence by engaging users on the platform and publicly displaying their cultural capital and personal taste (McQuarrie et al., 2012; McQuarrie & Phillips, 2014).

Instagram terms these influencers "creators" and describes Instagram as a platform in which creators can "turn their passions into livelihoods" (Instagram Business Team, 2019, para. 1). For instance, Instagram users Murad and Nataly Osmann rose to almost instant popularity in 2011 after a photo Murad posted of the couple went viral (Forbes, 2017). The image featured Nataly holding Murad's hand and leading him through the streets of Barcelona. The couple turned one Instagram photo and their love of

traveling into a career and are now considered one of the top travel influencers. By garnering a large, dedicated audience, these ordinary consumers can become social media influencers whose followers view them as trustworthy sources of advice (Vrontis et al., 2021).

Building on the two-step flow model (Katz & Lazarfeld, 1955), social media influencers can be defined as socially distinct opinion leaders who influence consumers' attitudes and behaviors through digitally spread word of mouth (Lin et al., 2018). As content creators, these influencers have expertise in a niche content area (Lou and Yuan, 2019). Their influence is derived from their social prestige, personal appeal, and expertise (Lin et al., 2018). Due to their impact on the consumer decision journey, these social media influencers can be used as a promotional tool by companies and organizations in a strategy called influencer marketing (Vrontis et al., 2021). Through sponsored content, social media influencers can earn money or free products by partnering with a brand and promoting their products and services. These trusted tastemakers are viewed as modern-day marketing commodities that can be used to endorse and promote products and services to their mass audience (De Veirman, Cauberghe, & Hudders, 2017; Vrontis et al., 2021). Influencer marketing is booming due to the fact that the endorsement is subtle and blends into the native feed and can reach a large audience through a multiplier effect (Wu et al., 2018). Consumers believe that these sponsored posts are genuine recommendations, which results in perceptions of message credibility and positive effect toward the endorsed brand (Lou & Yuan, 2019). Influencer marketing has become a $10 billion industry in 2020, and business-to-consumer firms are leaning more on influencer

marketing and are seeking collaborations with popular platform users to drive their marketing campaigns (Haenlein et al., 2020).

By partnering with an influencer, brands are trying to capitalize on the influencer's popularity and reach their captivated, niche audience (Yurieff, 2019). An influencer is typically evaluated, in part, on their engagement rates (Troesch, 2019). Engagement is based on quantitative success metrics such as the number of followers, likes, and comments the influencer accrues (De Veirman et al., 2017; Grave, 2019; Troesch, 2020). Within influencer marketing, the digital trace of other user's interactions with a post is an important element to consider (Wu et al., 2018). Both liking and commenting on a post are considered recorded interactions that are visible to other users. In general, these digital traces may encourage mimicking behavior due to herd mentality. For example, viewing that others have commented or liked particular content may influence the user to follow other's behavior and also interact with the post (Wu et al., 2018). Burnkrant and Cousineau (1975) argue that "one of the most pervasive determinates of an individual's behavior is the influence of those around him" (p. 206). Similarly, Watts and Doods (2007) argue that it is the large mass of individuals that drive influence rather than the influencer themselves. Therefore, the visibility of support from followers is how influencers gain and grow their power. Yet, what happens if these digital traces of support and interaction are no longer visible?

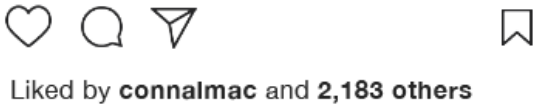
1.1.1 Instagram Platform Updates

On July 17, 2019, Instagram (2019a) announced that it began testing the removal of a visible like count on posts for some profiles within the following countries: Australia, Brazil, Canada, Ireland, Italy, Japan, and New Zealand. As of November of

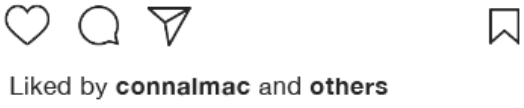
2019, Instagram (2019b) expanded the test of a hidden like count globally. Users affected by the test no longer saw the total number of likes or views on posts and videos from other users that appear in their feed. Instead of focusing on the visible number of likes, the like display will now feature the name of someone in the user's friend list who has liked the post. If a user's friend has liked the post, the individual will see the phrase "Liked by [friend's account name] and others" (Yurieff, 2019). See Figure 1 for a display of the difference.

Figure 1 Differences in Like Display

Visible Like Display



Hidden Like Display

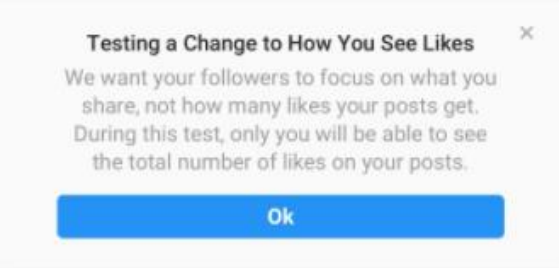


Note. The figures demonstrate the difference in like display. Both the current and exploratory hidden like displays will show the user if someone in their friend list has also liked the post. The only difference between displays is the presence of numbers.

The company explained their reasoning for the test through a Tweet: "We want your friends to focus on the photos and videos you share, not how many likes they get" (Instagram, 2019a). The function of liking a post will remain the same during testing. Users can still like a picture or video by clicking on the heart icon or double-clicking on the post. The only change will be the visibility of the number of likes that a picture or video has received. Users within the testing population will not be able to see how many likes one of their friend's posts has received; however, Instagram users can still see the

number of likes their own posts have earned by tapping on the list of people who have liked it (Instagram, 2019a). Users who are affected by this change received a notification at the top of their Instagram feed as shown in Figure 2. The disappearance of the public like count may fundamentally change the way users engage with the photo-sharing platform, as the number of likes a post obtains is the primary method through which content is evaluated (Booth & Matic, 2011).

Figure 2 Notification to Users in the Test Population



Note. The figure demonstrates the notification the users who are in the test population would see at the top of their Instagram Feed. The notification explains the platform's reason for the test, as well as how the test will change the user's experience on the platform. (Instagram, 2019a)

Instagram noted that the feedback from early testing has been positive, yet there is no indication by Instagram as to how "positive" was measured (Instagram, 2019b). What metrics is Instagram utilizing to measure the effects of the non-visible like count display? The measure most likely pertains to Instagram's recent effort to reduce the pressures of being perfect on social media. Through a partnership with the Jed Foundation, Instagram (2020) released a toolkit to help free users from the pressure to conform to standards seen on the platform. The toolkit walks readers through different scenarios that may occur on

Instagram and helps users become self-aware of their behaviors and emotions when engaging with the platform. The toolkit is separated into three main sections that focus on (1) how to decide what content to share and to whom, (2) how to maintain perspective when comparing one's self to others, and (3) how to help someone online who seems to be distressed. Within the conversation of how to maintain perspective, the toolkit encourages people to move past comparing themselves to others and look for self-validation rather than approval from others signified through the number of likes and comments that a post receives. Therefore, the removal of a visible like count by Instagram is meant to de-incentivize earning likes among users and help Instagram accomplish its mission of reducing the pressure of being perfect.

While the removal of a visible like count may be positive in relation to the efforts to reduce the pressures of being perfect on social media, it is important also to consider how the change affects influencers. Engagement (i.e., likes and comments) with posts is "a visible form of social currency" that documents the influencer's status and success (Cotter, 2019, p. 907). Influencers have stated their growing concerns about how the update will drastically change how brands select influencers to work with. For example, Sam McAllister, an Irish influencer with over 23,000 followers on Instagram, is worried that with the removal of a visible like count, the engagement rate will be replaced and "the number of followers a user has now defaults to be the main metric" (Yurieff, 2019, para. 4). Similarly, Felicity Palmateer, a professional surfer and Instagram influencer with 184,000 followers, stated she was worried that hiding the like count would add increased strain and difficultly on aspiring influencers who are trying to break into the industry (Yurieff, 2019). Since social media influencers are concerned with remaining

visible in users' feeds, they prioritize generating engagement and increasing followers to remain relevant based on the platform algorithm (Cotter, 2019). Therefore, the change in visible user engagement worries influencers, as the tactics that they once learned to garner engagement, may no longer help them gain visibility and influence. Instagram (2019b) admitted that they know the alteration of the like count display is a major change for creators; therefore, the company is looking for alternative ways to communicate value to potential partners.

Yet, Instagram (2019b) only addresses part of the problem—looking for alternative ways for influencers to communicate value to potential partners. It is also important to consider how this change in visibility of likes on Instagram posts will influence users and impact consumers' evaluations of influencers. How will influencers communicate value to potential followers who discover them since the visible like count is a metric that is currently used to persuade newcomers who are just discovering their accounts? A large number of likes indicates to the newcomer that the unfamiliar account in question is supported by a visible number of other accounts. Without a visible like count, this symbol of popularity and support disappears. One would assume that comments left by other users would then be used as a tool to evaluate an influencer's popularity as another user engagement metric. However, comments do not always appear alongside Instagram posts. For example, comments are not visible on pictures and videos within the Explore page, the central area from which users can find new accounts to follow based on their previous likes and interests (Instagram Press, 2019).

The Explore page is a grid of curated pictures and videos populated on a user's screen based on what the user has viewed and interacted with before (Instagram Press,

2019). Due to the personalized nature of the Explore page, the feature allows accounts to gain more exposure among people who are not currently following the account but are likely interested in the content. Therefore, influencers and brands engaging in influencer marketing strive to appear on the Explore page to build brand awareness and gain new followers. If a user is interested in the image they see on the Explore page, they can click on the image to view the entire post. While the post will predominantly look the same as it would appear on the user's main feed, there is one difference: the post on the Explore page does not include a visible comment display that showcases the number of comments the post has received or a link to expand all of the comments into a viewable list. Instagram does not explain why comments are not visible on the Explore page, however, the difference in the visibility of user-generated comments on the main feed and the Explore page is an interesting platform design element to study. It is of particular interest due to the different purposes of the main feed and the Explore page. Therefore, the study seeks to address the following research question: *How will varying levels of visibility of user engagement (i.e., likes and comments) influence user's evaluations of unknown social media influencers on the Explore page of Instagram?*

1.2 Purpose of the Study and Significance

Previous social media studies have shown that specific features of the user profile influence and affect other users in the same social network (Wu et al., 2018). The user profile is made up of three sources of content: content type, digital activity trace, and third-party contributions (Ellis and Boyd, 2013, as cited by Wu et al., 2018). It is the purpose of this study to evaluate how the visibility of digital activity trace in the forms of user engagement on an influencer's post affects other users who come upon the post at a

later time. This study will specifically examine individuals' information processing of an Instagram post from a social media influencer on the Explore page and their potential reliance on user-generated engagement to evaluate the influencer's credibility. With a move toward de-incentivize earning likes (Instagram, 2020), it is important to understand the impact of the visibility of user engagement such as comments and likes. The purpose of this research is to analyze how varying levels of count visibility for likes and comments will affect Instagram users' perceptions of the source credibility of unfamiliar influencers.

The study will examine the perceived source credibility of influencers when the visibility of the like count display (i.e., hidden, approximate, and an exact display) and comment count display (i.e., hidden and exact display) are manipulated. The study seeks to evaluate source credibility due to its effects on behavioral outcomes. For example, Breves and colleagues (2019) found that higher levels of perceived source credibility are directly connected to higher levels of positive behavioral intentions of consumers. Similarly, Lou and Yuan (2019) found that an influencer's credibility positively affects brand awareness and purchase intentions. Therefore, understanding how user-generated engagement visibility as a form of social information affects source credibility evaluations of social media influencers will help establish influencer marketing best practices for increasing positive behavioral intentions. Additionally, this research seeks to offer practical recommendations for influencers regarding maintaining or gaining influence on the social media platform after Instagram expands the hidden like count to all users.

As influencer marketing increases in practice, so do academic interests (Vrontis et al., 2021). Yet, research on influencer marketing is fragmented and needs continual focus as platforms evolve (Vrontis et al., 2021). This study is particularly important due to its practical application following the testing of the removal of a visible like count. While Instagram is the first platform to test the removal of a visible like count, it is not the only social media platform to engage in testing. Instagram's parent company, Facebook, is also testing the removal of a visible like count in a crucial attempt to overcome the power of likes and its influence on affirmation-seeking behavior (Constine, 2019). The test, which hides the like, reaction, and video view count, began on September 27, 2019 in Australia (Constine, 2019). In an interview with a Facebook spokesperson, TechCrunch reported that the test would be evaluated on whether people's sense of wellbeing improves in the test environment without substantially harming the user's engagement (Constine, 2019). While the apps are different, this move to test the removal of visible user-generated engagement metrics is a crucial change to the structure of social media. If two of the social media giants choose to hide engagement metrics, other social media platforms may follow suit. Therefore, the findings from this study prove immensely valuable in restructuring social media platforms to prioritize others' wellbeing.

Specifically, within the literature on social media influencers, the heuristic systematic model is rarely used (Vrontis et al., 2021). Yet, it is a valuable theory to continue studying within the context of social media due to consumer's reliance on minimizing cognitive and time restraints when processing information. For example, Metzger and Flanagin (2013) argue that entertainment information during casual searches tends to rely on heuristic processing rather than systematic processing. Therefore,

individuals on the Explore page of Instagram are more likely to rely on general rules of thumb, known as heuristics, when deciding if a source is credible and should be followed on the platform. The study will specifically rely on the MAIN Model to investigate the effects of heuristic cues on credibility evaluations of influencers.

The MAIN Model suggests that four technical affordances can be relied on to form perceptions of credibility when engaging in heuristic processing: modality (M), agency (A), interactivity (I), and navigability (N) (Sundar, 2008). These affordances are part of the structural features of the social media platform. Within the present study, likes and comments are evaluated as affordances that can cue heuristic-based judgments. While the initial use of the Main Model is focused on evaluations of content credibility, this study expands its applicability to include the evaluation of source credibility through the utilization of the warranting principle. The warranting principle argues that individuals rely on cues to judge the self-presentation of others within computer-mediated communication (DeAndrea, 2014). Based on the warranting principle, impressions are more heavily shaped by information that the source cannot control such as the volume of user-generated engagement (i.e., likes and comments). Thus, the present study argues that the like and comment count displays are media platform affordances that are high in warranting value and can trigger heuristic judgments related to source credibility. Therefore, this study will provide greater understanding of how social media influencers impact consumer behavior based on the visibility of user engagement when employing heuristics to process information found on Instagram posts. Similarly, this study also contributes to credibility literature by examining the heuristics utilized to form credibility judgments of unknown individuals within a computer-mediated context.

Sixty percent of Instagram users in the United States are under the age of 34 (Haenlein et al., 2020). Marketers striving to reach younger consumers must look to Generation Z and Millennial's media consumption patterns in order to effectively reach them (Haenlein et al.. 2020). In an attempt to reach consumers through mobile advertising, firms are relying more heavily on influencer marketing (Haenlein et al., 2020). A recent survey by the Association of National Advertisers (2018) found that Instagram is the single most important channel for influencer marketing, with Facebook falling right behind. The Association of National Advertiser's CEO, Bob Liodice, stated that "a growing number of marketers are turning to influencers to help them combat ad blocking, leverage creative content in an authentic way, drive engagement, and reach millennial and gen Z audiences who avidly follow and genuinely trust social media celebrities" (ANA, 2018, para. 5). Specifically, during the Covid-19 pandemic, influencer marketing was at an all-time high on platforms such as Instagram and TikTok due to increases in influencer engagement and higher rates of social media usage (Beganovich, 2020). With 58% of Generation Z and 48% of Millennials reporting that they have purchased something an online celebrity has recommended (Ypulse, 2020), it is important to expand research on influencer marketing among Generation Z and Millennials, specifically while taking current Instagram platform changes into consideration. This study specifically examines the perceptions and behavior of Generation Z Instagram users when viewing a post by an unknown influencer on the Explore page once a visible like count is removed and tests the importance of a visible comment count. This study provides valuable information on how Generation Z users perceive an unknown influencer's credibility and develop relationships with influencers.

Thus, the research offers practical recommendations for influencers regarding maintaining or gaining influence on social media platform when the like count is hidden.

CHAPTER 2. REVIEW OF THE LITERATURE

2.1 Overview

The previous chapter established the significance of this study and the research objective, which is to examine the effect of visible user-generated engagement displays on Instagram user's credibility perception of unknown influencers discovered through the Explore page of the platform. This chapter will discuss the context of the study by describing the functionality of Instagram and how its technological affordances shape individuals' interactions with the platform. Additionally, this chapter provides an overview of relevant research surrounding decision making within a computer-mediated and focused on outlining heuristic cues within the heuristic systematic model and the MAIN model as well as warranting cues within the warranting principle. The chapter concludes by stating the key research question and hypotheses for this study.

2.2 Functionality of Instagram

In order to truly understand the persuasive implications of social media, it is important to consider the technological affordances of social platforms (Bayer et al., 2020). Instagram as a platform promotes interaction with posts through the liking, commenting, and sharing features. Additionally, the posts that an individual sees are curated by an algorithm that prioritizes interests and higher engagement (Carter, 2019). These features have major implications guiding how users interact with and consume media on Instagram. These features include engagement metrics which drive interaction, a platform algorithm that populates a user's feed with personalized content, and the platform's ability to connect individuals with similar interests through the Explore page.

2.2.1 Interaction Drives Engagement Metrics

The study of social media platforms requires looking at the distribution of interpersonal communication to large audiences and the social interaction that ensues (Bayer et al., 2020). As Carr and Hayes (2015) describe, social media is "Internet-based, disentrained, and persistent channels of masspersonal communication facilitating perceptions of interactions among users, deriving value primarily from user-generated content" (p.50). Therefore, it is the social interaction with others that users find value in (Bayer et al., 2020). This interaction occurs as users engage with posts. Primarily, interaction takes the form of liking or commenting on other user's post. If interaction through likes and comments were not intertwined as a central component of the platform experience, users might not have found value in its use.

Interaction on social media occurs across networks. Bayer et al. (2020) described networks as a platform-specific element that symbolizes a social connection. One's network is made up of individuals with who the user has formally connected. In the case of Instagram, one's network is comprised of those who the individual follows as well as those who follow the individual. This network is visibly represented by the searchable list of connections (Boyd & Ellison, 2007). Those within a network are able to consume and engage with user-generated content that appears in their feed (Bayer et al., 2020). Therefore, network connections are visible beyond the following and follower list on each user's profile; connections can also be viewed on individual posts through engagement metrics. Before the testing of the hidden like count, when a user liked a post, the action would be visible to anyone who can see the post by clicking on the "liked by" link. This link allows users to view a list of all the accounts who have interacted with the

particular post. The list includes the profile picture and username of each account who has liked the post.

Similarly, when a user clicks on "view all comments," they will be able to see all the comments that were left on a post and who wrote them. It is important to note that Instagram prioritizes displaying certain comments over others when there is a high volume of comments. With comment previews, the individual who posted the content selects one or two comments to highlight at the bottom of the post, while condensing all of the other comments and hiding them behind the phrase "view all comments."

2.2.1.1 Likes and Comments

The like feature functions as a counter that visually showcases the total number of likes garnered as well as a list of who has liked the shared content (Gerlitz & Helmond, 2013). Users can look at not only the number of likes that a post has received when making judgements about a post, but who in particular has liked the post. Gerlitz and Helmond (2013) suggest that the like feature is a fleeting affirmation to track a user's interaction with content (Gerlitz & Helmond, 2013). While creators of social media platforms will argue that social buttons are for connecting and creating community, the importance of these features for measuring engagement and data mining cannot be denied. One single like may prompt an additional like. It is a chain of interactions in which the potential for more likes, comments, and shares grows with each like. The platform is specifically designed to strategically expose likes in an effort to encourage further interactions among users (Gerlitz & Helmond, 2013).

The feature of likes on Instagram essentially structures what is worthy through the number of likes it garners (Ross, 2019). This occurs through the quantifiable nature of the

like button which functions within what Gerlitz and Helmond (2013) refer to as the like economy: “an infrastructure that allows the exchange of data, traffic, affects, connections, and of course money, mediated through Social Plugins and most notably the Like button” (p. 1353). As a symbol within the platform, the comparable nature of likes leads to metrification of users’ affective response to content and further intensifies users’ actions by generating traffic and engagement (Gerlitz and Helmond, 2013). “Each click on a Like button is supposed to lead to more traffic for, and more engagement with, web content, as friends or likers are likely to follow their contact’s recommendations or might be influenced by what their friends like” (Gerlitz & Helmond, 2013, p. 1358). A post’s value, and therefore how other users view the post, is based on the amount of likes it receives (Ross, 2019). With each like that is accumulated, more value is added. While likes are described as a way to socially connect with other users on the platform, they also function as data that allows for the tracking and measuring of user engagement which others can rely on to form judgements (Gerlitz & Helmond, 2013).

Ross (2019) found that Instagram users will look to their followers to estimate how many likes a post should get within the first few minutes after it has been posted. If their expected number of likes is not reached, the user assumes that the post is not valuable and takes it down. While Ross (2019) examines the effect of likes from the poster’s point of view, the implications can be applied to general users as well. If users are taught that likes have value and are equivalent to signs of support and popularity, they may evaluate other’s posts based on the number of likes the post receives. For example, posts with fewer likes may be viewed as less valuable than posts with a larger number of likes. Therefore, users rely on the statistical nature of likes to measure popularity. Likes

function as a recommendation or social validation. The more a post is liked, the more recommended it is perceived to be.

Comments on social media posts are normally "short statements of personal opinion" left on another user's post (Peter, Rossmann, & Keyling, 2014, p. 19). Peter et al. (2014) argue that comments are direct social information as each comment conveys an individual recommendation. The comment's meaning can be easily deduced and utilized to evaluate information. In contrast, likes, which symbolize an aggregation of evaluation, are considered indirect information that can indicate different meanings based on the individual's motivation (Peter et al., 2014). For example, liking a post could signify acknowledgments, support, or a positive attitude toward the content or message creator. While a like on a post does not convey a recommendation such as a comment, a like can represent the overarching public opinion regarding the post.

2.2.2 Content Display is Personalized

Social interaction is not the only platform feature that is important to consider. It is also important to consider the reasons that users engage with a particular platform over others. Facebook, for example, is primarily used to stay in touch with family and friends that represent offline relationships, while Twitter is used as a news feed that allows consumers to select the news content that they would like to stay up to date on (Haenlein, 2020). Instagram, on the other hand, is used as a form of entertainment that allows users to browse interesting visual content while filling free time (Haenlein, 2020). Users open Instagram and dive into a world of computer-mediated communication contingent on photo and video sharing.

Instagram is designed to capture the user's attention and keep the user entertained by feeding them personalized content. A user's feed is populated with posts made by accounts that the user chooses to follow primarily based on their entertainment value (Haenlein, 2020). The posts are organized based on an algorithm that the platform is programmed to follow that prioritizes relevancy over recency and provides a unique feed for each user based on their previous interactions on the platform (Constine, 2018). Relevancy is determined by three main factors: the user's predicted interest in the content based on past behavior on the platform, the relationship that the user has with the person who shared the content, and the recency of when the post was shared (Constine, 2018). Therefore, priority is given to posts that have similar content to what the user has engaged with in the past, are made by accounts the user frequently interacts with, and are timely (Constine, 2018). Instagram curates what each user sees based primarily on the individual's past viewing habits and behavior on the platform (Johnston, 2016) to avoid burying the interesting content in a stream of irrelevant posts.

Additionally, three factors related to the user's behavior can influence what a user sees: the frequency of use, the duration of use, and the number of followers a user has (Constine, 2018). Each time a user opens Instagram, the platform repopulates to show the user the most relevant posts since they last visited. If the user is scrolling for a long time rather than engaging in short sessions, the algorithm will have to dig deeper into the collection of content to fill the user's total browsing time. The number of followers a user has may also influence what their main feed looks like. The more followers an individual accrues, the more content the algorithm must choose from, meaning their main feed will

be populated with a wider breadth of content. This results in seeing a wide array of content from multiple users and seeing less content posted by any specific person.

Individual's Instagram feeds used to be populated based solely on timeliness. What was posted most recently appeared at the top of the feed. The change from a reverse-chronological feed to an algorithmically sorted feed resulted in content creators seeking out ways to be prioritized based on the new algorithm. Individuals looking to gain followers must now find ways to optimize their posts and increase their likelihood of appearing more frequently (Constine, 2018). This change also creates a more persuasive platform design with the generation of engagement and maintenance of attention the main goal (Johnston, 2016). With posts now prioritized based on the level of interest, users will be more likely to use the platform for a longer period of time and keep scrolling as their interest is better maintained. The more scrolling a user does, the more likely they will come across posts from individuals they are unfamiliar with and will need to make a judgment. This primarily occurs through Instagram's design of connecting people with similar interests.

2.2.3 Connecting People Across Similar Interests

Instagram prides itself on brings users closer to the people and content they love (Instagram, n.d.). One way to accomplish this is by finding new content that users perceive as valuable entertainment (Haenlein, 2020). There are two primary ways to discover new accounts: through suggested posts on a user's feed or utilizing the Explore page to view posts or short videos called Reels (Instagram Press, 2020a). As stated previously, the content that appears in all of these options is optimized to showcase content that fits the user's specific preferences (Constine, 2018).

2.2.3.1 Suggested Posts in Feed

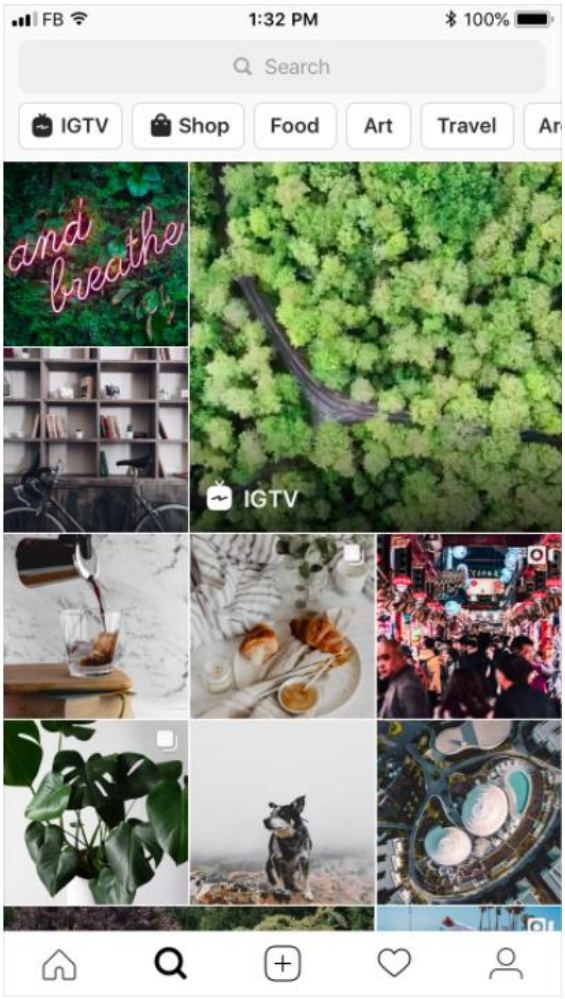
If a user scrolls through all of the new posts from accounts they follow, they will reach a block populated by Instagram that states they are “all caught up” (Instagram Press, 2018b). From there, users can choose to view past posts that are older than three days or scroll through suggested posts that Instagram has curated based on posts the user has previously liked or saved and accounts that the user currently follows (Instagram Press, 2018b). Since these posts are based on user data, suggested posts can connect users with accounts and interests that matter to them. Each suggested post states why it was selected for the user. Directly from the suggested posts, users can tap on a blue button to follow the account. However, the suggested post can be seen as an interruption or feel invasive if the user is not actively searching for new accounts to follow (Felicitas, 2020).

2.2.3.2 Explore Page

Due to the data collected through past interactions, users do not have to actively search for content that fits their interests; instead, Instagram presents personalized content to the user (Gerlitz & Helmond, 2013). Instagram organizes its content based on titles, hashtags, and geotags, creating of a “multiverse of interest pockets” available through the Explore feature (Johnston, 2016, para. 6). Instagram (2019) states that the Explore page is a way for users to discover new accounts that they do not already follow that are relevant to their interests. When visiting the Explore page, users can choose from a list of predetermined top channels (i.e., food, art, and travel) listed in the navigation bar (Instagram Press, 2019), as shown in Figure 3. The top channels are always after the shortcut buttons to reach IGTV and Shop. If an individual's specific interests do not fall into one of the predetermined top channels, they can use the search feature to find more

specific content that fits their needs. Each month, the Explore feature is used by more than 50% of Instagram accounts (Instagram Press, 2019). This means that users are frequently looking to the Explore page to expand their list of followers and are actively looking to connect with accounts that pertain to their interests. Since users make an active decision to visit the Explore page to find new content, it will be the focus of this study rather than the suggested content on a user's main feed.

Figure 3 Updated Explore Page Display



Note. The image above is a screenshot of Instagram that shows the top portion of the Explore page from a mobile phone's point of view. The navigation bar is featured at the top of the image below the search feature. The navigation bar's top channels fluctuate (Instagram Press, 2019).

The Explore page is unique due to how its content is sourced. While posts appear in the Explore page based on the user's past likes and interest, posts also appear based on how a user's friends have previously engaged with a post (Carter, 2019). Thus, the likelihood of a post appearing on the Explore page increases as the number of user's

followers engaged with the post increases. This function creates a chain reaction for the post's reach. Therefore, high levels of engagement within specific niche areas will increase an influencer's chances of appearing on the Explore page and reaching prospective audiences. Yet, presence alone on the Explore page is not enough to persuade users to like, comment, and follow. Instead, users need to form their own judgement of the post and evaluate the credibility of the influencer before deciding how they are going to act (Berlo, Lemert, & Mertz, 1996).

2.3 Perceived Source Credibility

Within social media platforms, consumers encounter numerous influencer content from a variety of sources. Particularly within the Explore feature of Instagram, users are presented with a personalized feed of posts relevant to their interests and made by public accounts they do not already follow. In the case of this study, when an individual views a post on Instagram from an unfamiliar source, they will strive to make a judgement about whether or not to trust the presented information. This judgment is based partly on the evaluation of the message source (Berlo et al., 1969). Hovland and Weiss (1953) argued that the source of information is usually as important as the content when determining the impact of the communication. Particularly within marketing communication, the concept of source credibility is important regarding its effect on an individual's attitudes, behaviors, and intentions after receiving a promotional or persuasive message (Eisend, 2006).

The root of source credibility can be traced back to Aristotle who argued that persuasion is divided into ethos, pathos, and logos. Ethos can be described as the perceived credibility of an individual derived from evaluating the speaker's personal

character (Aristotle, 350 B.C.E./1992). Although termed ethos by Aristotle, the influence of a source on communication effectiveness can also be labeled source credibility (McCroskey & Teven, 1999). Within persuasion research, source credibility has been defined as an extrinsic, mental cue used when an individual processes information (Chaiken, 1987). Therefore, source credibility can be defined as the multidimensional attitude a message receiver forms about the message source, which subsequently affects the persuasiveness of the message (McCroskey & Young, 1981). This attitude is formed when the individual evaluates the communicator's perceived characteristics (Ohanian, 1990).

Built upon the source credibility model by Hovland, Janis, and Kelley (1953) and the source valence model by McGuire (1985), Ohanian (1990) created a multidimensional scale to measure celebrity endorser's perceived source credibility: trustworthiness, expertise, and attractiveness. Trustworthiness is the message receiver's "degree of confidence in, and level of acceptance of, the" source (Ohanian, 1990, p. 4), while expertise is the message receiver's perception of the communicator as having valid assertions (Hovland et al., 1953). Attractiveness is based on the message receiver's perception of the physical attributes of the source (Ohanian, 1990).

While attractiveness (i.e., classy, sophisticated, handsome, beautiful, glamorous, elegant, sexy, and charming) is a cue used by individuals to form initial judgments of others, it is based on the source's physical attributes; in contrast, trustworthiness and expertise are based on non-physical characteristics (Ohanian, 1990). The current study looks at how socially-based user-generated engagement functions as a cue that affects perceptions of credibility when viewing posts on the Explore page of Instagram. Images

that are often featured on the Explore page shortcuts of food and travel are primarily focused on displaying food items and travel experiences. In these instances, the source's physical attributes may not be known from the initial post. Users may have to go to the source's profile in order to view the source and make a judgment regarding attractiveness. Whereas this study is focused on the credibility judgments that are made when viewing initial posts on the Explore page of Instagram, the researcher decided to control for attractiveness by creating stimuli that did not feature the source and instead featured content that pertained to the areas of interest (i.e., travel and food). Thus, the attractiveness of the influencer is not of particular interest in the study, and this study focused on examining source credibility through the non-physical-characteristic dimensions: trustworthiness and expertise.

Persuasive messages on Instagram are important to examine due to the social context in which they are embedded. Social media is inherently social, and each message is shaped by the interactions of other users (Carr and Hayes, 2015). Therefore, it is important to consider how individuals form perceptions of trustworthiness and expertise within a socially constructed online environment. Particularly on the Explore page, users may be unfamiliar with the source of the post. In this instance, typical characteristics that are used to determine perceptions of credibility such as traditional credentials are not present (Vendemia, 2017). Sundar (2008) states that "cues embedded in—and transmitted by—the structure, rather than content, of digital technologies are likely to be particularly salient to today's youth" (p. 75). In essence, the technological affordances of the platform can influence an individual's credibility assessment (Sundar, 2008). On Instagram, technological affordances would include the aggregated display of social information in

the form of user-generated engagement such as likes and comments on a post. Therefore, the present study seeks to evaluate how the visibility of user engagement, based on the social information they convey, influences credibility perceptions of the unfamiliar sources.

2.4 Decision Making within Computer-Mediated Communication

To evaluate how user-generated engagement visibility can affect source credibility perceptions, it is first important to outline the processes that may influence a user's decision-making process. Below, the heuristic systematic model, MAIN model, and warranting principle are discussed in relation to their influence on how a user may engage in making a decision when viewing computer-mediated communication. Of particular importance are the cues within a computer-mediated message that may be relied on to form evaluations. Particularly within an online environment, traditional sources of social and physical cues may be lacking. So, it is important to investigate the technological affordances of the platform and how they function as cues for making credibility judgments.

2.4.1 Message Processing via the Heuristic-Systematic Model

Once a user gets to the Explore page, it is important to understand how they evaluate the message that they are viewing and form attitudes toward the influencer. This begins by understanding how individuals process a message. The heuristic-systematic model of persuasion describes two dual-processes in which a user can engage to form an attitude: heuristic and systematic (Chaiken & Ledgerwood, 2007a). The heuristic route is "a relatively fast, superficial, spontaneous mode based on intuitive associations"

(Chaiken & Ledgerwood, 2007a, p. 268). In contrast, the systematic route is "a more in-depth, effortful, step-by-step mode based on systematic reasoning" (Chaiken & Ledgerwood, 2007a, p. 268). The route in which a user engages depends on their ability and motivation to think carefully about information. Therefore, if an individual is motivated and has the ability (i.e., time, knowledge, mental capacity) to engage in intensive reasoning, they will most likely rely on the systematic processing route (Chaiken & Ledgerwood, 2007a). However, due to consumers' natural tendency toward frugality regarding their use of mental resources, heuristics can be relied on to form quick judgments rather than engaging in intensive systematic processing (Sundar, 2008).

In the heuristic route, the individual does not elaborate on content; instead, their attitudes and intentions are influenced by cues such as "the credibility of the communicator or on the level of consensus in the social environment" (Kumkale, Albarracin, & Seignourel, 2010, p. 1327). These cues, termed heuristics, are well-established guiding rule that can guide one's judgements (Tversky &Kahneman, 1974). A visible heuristic cue can trigger a judgment rule that is already stored in a consumer's memory and lead to quickly-made judgments that do not take into consideration the message content (Sundar, 2008). As a simple decision rule saved in one's memory, heuristics function as an intuitive shortcut (Chaiken & Ledgerwood, 2007a; Chaiken & Ledgerwood, 2007b) that helps individuals make a decisions quickly and efficiently. With little critical thinking, judgments made in the heuristic route are simply based on visible, easily-noticed cues (Chaiken & Ledgerwood, 2007a).

2.4.1.1 Factors Affecting an Individual's Tendency to Heuristically or Systematically Process

There are three criteria that predict the likelihood of the use of heuristics. First, the message receiver must be able to cognitively draw upon the heuristic cue in order to evaluate credibility (Sundar, 2008). Second, the judgment rule must be easily accessible to the user during the decision-making process, with the ease of accessibility increasing with rule's previous use and reliance (Sundar, 2008). Third, the judgment rule must be relevant to the specific decision being processed (Sundar, 2008). Therefore, familiarity with Instagram may influencer if and how someone relies on a heuristic cue.

2.4.1.1.1 FAMILIARITY OF PLATFORM AND HEURISTICS PROCESSING

Haim, Kumpel, and Brosius (2018) argued that heuristic cues based on portrayed popularity must be learned. Therefore, "the more experience users have with [platform specific cues], the better they are able to use them in their selection and navigation behavior" (Haim et al. 2018, p. 203). An individual's familiarity with Instagram, measured through frequency and time of use, could have practical implications for their likelihood to utilize a heuristic. For example, individuals who do not frequently use Instagram may not be familiar with user-generated engagement and its symbolic meanings. Thus, they may not utilize user engagement as a heuristic to help form their judgment of the influencer. In contrast, those who have prior experience relying on user-generated engagement to form evaluations may more easily access the heuristic rule and rely more heavily on it. For instance, Van Der Heide and Lim (2016) found that system-generated cues and consensus heuristics were more likely used among individuals who had a high familiarity with the platform. In contrast, unfamiliar users relied solely on consensus heuristics instead of utilizing system-generated cues.

Additionally, the relevance of a particular cue may vary based on the individual's interpretation (Haim et al., 2008). Frequent users of Instagram, may have garnered a large following and be used to higher levels of user engagement than those infrequent Instagram users. Therefore, frequent Instagram users may have a biased perception of how much user engagement a post should receive and perceive the same presentation of engagement as less favorable than infrequent users. This may result in lower perceived credibility scores between those who frequently and infrequently use Instagram. Therefore, it is important to control for how a user's familiarity with a platform and its technological affordances may influence whether they utilize a particular heuristic to form their credibility judgments (Van Der Heide & Lim, 2016).

2.4.1.1.2 Level of Involvement

The route of persuasion someone enters during message processing is based on the amount of issue-relevant elaboration they engage in (Sengupta, Goodstein, & Boninger, 1997). It's important to note that elaboration is based on the level of involvement. Therefore, one covariate that may change how individuals engage with an Instagram post is their level of involvement. The viewer's involvement with content can be conceptualized as attention allocated to a message and its source (Greenwald & Leavitt, 1984). This paper will try to control for the covariate of involvement by measuring the participant's level of involvement through the personal involvement inventory (Zaichkowsky, 1994).

2.4.1.2 The Bias Effect

Since individuals are "inclined to balance efficiency and accuracy in their judgments, [they will exert] as much effort as needed to develop a confident judgment"

(Kumkale et al., 2010, p. 1327). This means that some individuals may rely solely on applying relevant heuristics to attain the desired level of confidence to form a judgment (Kumkale et al., 2010). However, some individuals may engage in both forms of processing. The heuristic-systematic model argues that the avenues of processing are not mutually exclusive (Chaiken & Ledgerwood, 2007a). Therefore, an individual may engage in both heuristic and systematic processing. Yet, an individual's systematic processing can be biased by heuristics due to the potential interplay or reliance on both processes (Chaiken & Ledgerwood, 2007a).

Research shows that even when the motivation and ability to process information are high, heuristics cues can bias the direction of the systematic thinking (Chaiken & Ledgerwood, 2007b). Therefore, an enacted heuristic "can either directly lead to a snap judgment as in heuristic processing or serve to frame, bias, or otherwise guide more systematic processing of content" (Sundar, 2008, p. 75). Therefore, heuristics can function as a moderator that can "amplify or diminish content effects on credibility" (Hillgoss & Rieh, 2008, p. 1468). Thus, even if a user engages in systematic processing of an Instagram post's content, the heuristics cues on the post may bias the systematic thinking.

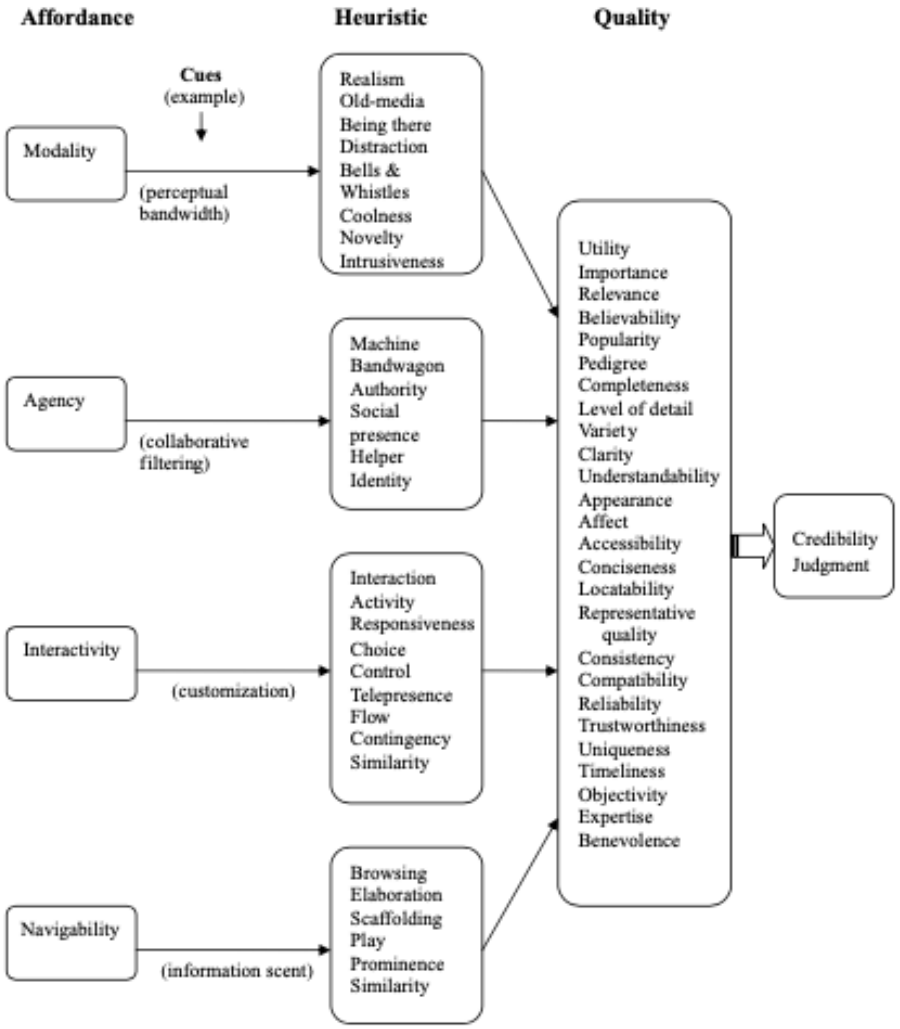
2.4.2 Heuristic Processing and the MAIN Model

Based on the heuristic systematic model, Sundar (2008) argues that individuals who heuristically process information utilize credibility markers embedded in media which indicate expertise and trustworthiness (Sundar, 2008). As mentioned previously, these heuristics allow "message receivers to make loose associations between the cue and the message" (Sundar, 2008, p. 74). The MAIN Model, which stands for modality,

agency, interactivity, and navigability, was established as a way to explain how individuals evaluate messages transmitted through internet-based media (Sundar, 2008). The model focused on explaining how technological affordances of digital media can be used as a heuristic cue. Sundar (2008) defines affordances as "a particular capability possessed by the medium to facilitate a certain action" and defines a cue as "anything in the digital media use that might serve as a trigger for the operation of a heuristic" (p. 79). It is important to note that these affordances must be noticed by the message receiver in order for the cue to serve as a trigger for heuristic processing.

Sundar (2008) claims that there are four main types of technological affordances in which cues can be embedded: modality, agency, interactivity, and navigability (See Figure 4). First, modality represents the particular structure in which the message is presented; whereas the message may be in a singular modality (i.e., text or audiovisual) or a combination (Sundar, 2008). Second, agency cues revolve around the signals that help the message receiver uncover the message source, ranging from a particular person, organization, the computer itself, to an aggregate of other users who suggest content (Sundar, 2008). Third, interactivity is concerned with how media grants interaction and activity and thus personalization which enhances a user's positive "feelings about the uniqueness, timeliness, reliability, and relevance of the information exchanged, all of which are likely to positively impact credibility perceptions" (Sundar, 2008, p. 88). Fourth, navigability regards the interface features that allow for transportation from one message to another such as hyperlinks (Sundar, 2008).

Figure 4 The MAIN Model



Note. This figure showcases the four affordances of Sundar's (2008) MAIN Model and highlights how each affordance leads to a credibility judgment.

Of particular interest in this study is the technological affordance of agency cues, which includes the aggregate of other users who filter and suggest content. In this case, other users' behavior is evaluated based on the bandwagon heuristic which indicates a collective endorsement of the content (Sundar, 2008). "The endorsement-based heuristic suggests that people are inclined to perceive information and source as credible if others

do so also, without much scrutiny of the site content or source itself" (Metzger et al., 2010, p. 427). In this sense, the assessment of credibility can be socially constructed based on what others think rather than independently formed. Therefore, it is important to evaluate the effect of aggregated and socially constructed information on Instagram.

2.4.3 User-Generated Engagement as a Cue that Prompts the Bandwagon Heuristic

Metzger and colleagues (2010) conducted focus groups to gain a deeper understanding of the credibility assessment process. The results showed that individuals utilize social information in the form of heuristics to form credibility judgments. One of the main heuristics that individuals rely on are endorsement-based, bandwagon heuristics, including ratings and reputation systems produced by the platform's technological affordances. Within web-based platforms, it is common for individuals to rely on socially produced information to form credibility assessments because people cannot always expend the time and energy required for systemic information evaluation" (Metzger et al., 2010, p.435). Likes and comments function as socially based ratings that signify a communal acceptance or trust in the poster and promote the poster's reputation to others.

Heuristics can appear in both the message as well as the presentation of the communication (Sundar, 2008). Sundar (2008) explains that each type of technology has set capabilities that both shape the content itself as well as how it is presented in the platform. For Instagram, content is presented as a photo or video. Within the post, the source's profile picture and username are at the top right and social buttons, including the like and comment display, are underneath the content. Each technological feature of the platform has the potential to be viewed as a cue that "may aid judgments through triggering heuristics about the typical nature of underlying content" (Sundar, 2008, p. 75).

On Instagram, attention and appreciation are awarded through participatory social buttons such as the like button which the user actively clicks or the comment button which the user clicks to open a keyboard to add commentary to the post. User-generated engagement is valuable as it produces visible data that others can use to form judgments. However, it is the platform that decides which engagement actions can be performed and which produce visible, comparable data (Gerlitz & Helmond, 2013). On Instagram, the platform promotes the function of likes, comments, and share, although shares differ from likes and comments as the list of who has shared a post is not visibly displayed as a list. Thus, the features of likes and comments are aggregated displays of how other users have interacted with the content and can be defined as socially constructed agency cues.

Visible user-generated engagement in the form of likes and comments can be defined as "metric information about users' behavior or their evaluations of entities" (Haim et al., 20018, p. 188). Individuals can look toward the aggregated display of social support when trying to evaluate the post and form a credibility perception by relying on the bandwagon heuristic. When a viewer sees a bandwagon cue, they can utilize the rule "majority opinion is correct" to form a judgment. Bandwagon cues that are externally produced by users, such as likes and comments, suggest the content is supported and endorsed by many others, which subsequently impacts impression formation (Engelmann & Wendelin, 2017; Haim et al., 2018). Therefore, indicators of collective endorsements can trigger heuristics pertaining to social consensus and popularity (Sundar, 2008). Communication with a stronger social consensus has been found to be viewed as more persuasive than communication with a weaker social consensus (Kumkale et al., 2010).

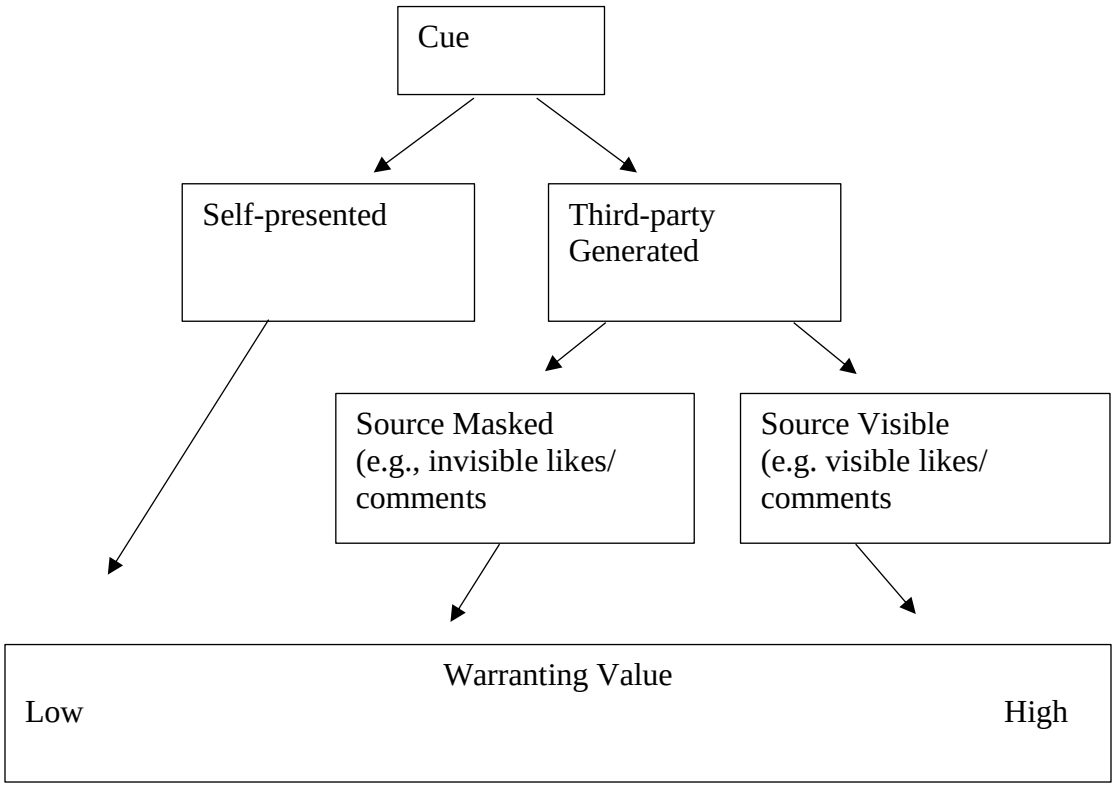
McGlynn et al. (2019) evaluated variables of Instagram profiles that "prompt heuristics associated with trustworthiness" and predict judgments of trust and found that cues related to other's social endorsement (i.e., number of likes, comments, and followers for an account) of the post were a primarily factor (p. 344). Within the study, the heuristic cues symbolizing social endorsement explained 33.40% of the variance in trust. The author rationalized that since these endorsements were made by others and thus outside of the control of the profile owner, they prompted more trustworthiness associations. Therefore, the significance behind social endorsements comes from the warranting value in which they present, discussed in detail in the next paragraph.

2.5 Warranting Principle

Instagram users look for cues to determine the source credibility of the public profile when they possess no prior knowledge about the individual. Since claims can easily be fabricated on social media, the warranting principle can be used to understand how individuals evaluate online self-presentations (DeAndrea, 2014). The warranting principle argues that individuals rely on cues to judge the self-presentation of others within computer-mediated communication, such as Instagram (Walther & Parks, 2002). Any cue that authenticates an online self-presentation is referred to as a warrant, and warranting value refers to the extent that someone perceives the information as immune to the source's manipulation (DeAndrea, 2014). The theory posits that third-party cues which the source cannot manipulate or control are more heavily relied on than self-descriptions (Walther et al., 2009). Third party cues include user-generated content, which can function as "an important warrant or signal that information is valid and reliable" (Flanagin and Metzger, 2013, p. 1628).

Yet, the value of third-party information in forming judgments can be reduced. DeAndrea (2014) notes that "when there is reason to question whether or not the source of information truly is a third party" the warranting value is reduced (p. 191). Masking the source of information can have a negative effect on warranting value and an individual's perceptions of the source. If the individual can not verify the genuine source of information, the warranting value of the third-party information is lowered. See Figure 5 for a visual display of the warranting principle.

Figure 5 The Warranting Principle



2.5.1 Hypothesis Formation

This study draws on the heuristic systematic model to help predict the formation of source credibility perceptions when individuals heuristically process the information on

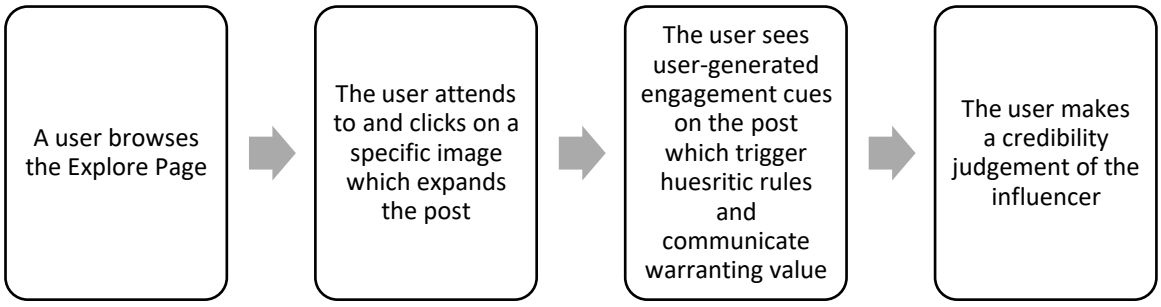
Instagram. Younger individuals who frequently use social media are highly likely to utilize bandwagon heuristics to form credibility judgments (Sundar, 2008). Particularly when "no other information of greater diagnostics is available at the time," individuals will rely on heuristic cues to form an attitude (Kumkale et al., 2010, p. 1348). Therefore, if the message itself contains minimal evidence or argumentation, heuristics will be relied on even if the message recipient is able and motivated to process systematically (Kumkale et al., 2010, p. 1348). Many posts populated on the Explore page do not contain high levels of evidence or argumentation. Therefore, Instagram users are likely to rely on user-generated engagement as a heuristic cue in order to make quick decisions regarding information quality and credibility (Sundar, 2008).

Based on the MAIN model, user-generated engagement in the form of a like and comment count is considered an agency cue that can lead to source credibility perceptions (Sundar, 2008). Since they are aggregated displays of other user's behavior, the features are treated as collective endorsements of the content and the bandwagon heuristic is relied on (Sundar, 2008). Therefore, since others have supported the post through likes and comments, the message receiver will be inclined to perceive the source as credible (Metzger et al., 2010, p. 427).

Drawing on the warranting principle, the researcher argues that user-generated engagement can be defined as a third-party cue since it is the aggregation of user-generated information. As argued by Flanagin & Metzger (2013), as the amount of information aggregates, it is more difficult to fake and the influence is magnified. Therefore, aggregated displays of user-generated engagement should be valued more highly than self-presented information and will most likely be relied on by individuals

when forming credibility evaluations. See figure 6 for a visual representation of the hypothesized process.

Figure 6 Heuristic Processing of Instagram Posts on the Explore Page



Note. This model illustrates how those who have a high prior experience and low personal involvement heuristically process Instagram post on the Explore Page

In their study on expert- versus user-generated ratings online, Flanagin & Metzger (2013) found that the volume of user-generated movie ratings acted as a warranting cue. The study shows that as the volume of user-generated ratings increased, people "demonstrated greater levels of (a) perceived information credibility, (b) reliance on the information, (c) confidence in information, (d) the congruence between their own and other's personal evaluations of the information and (e) its influence on their behavior will increase" (p. 1630). Thus, high volume functions as a warrant that leads to information trust. In the case of Instagram, likes and comments can be viewed as aggregated information presented by the computer system, or in this case, the platform. The system presents the collection of likes and comments in the form of a statistic tally (DeAndrea, 2014). Therefore, visible like counts and comment counts function as an aggregate user-representation. As the amount of information aggregates, it is more difficult to fake and the influence is magnified (Flanagin & Metzger, 2013). Therefore, it is hypothesized that

individuals engaged in heuristic processing will use the aggregated user-representations of likes and comments as warranting cues to make judgements of the source credibility.

The present study seeks to evaluate if platform-related factors, such as social influence through the presence of a visible display of a collective endorsement affect source credibility evaluations of influencers on Instagram. Based on the aforementioned information, the following hypotheses have been formed regarding the main effect of likes and comments, respectively, on source credibility:

H1a: Influencer posts with an approximate like count display will be perceived to be more credible than influencer posts without a visible likes count display when controlling for Instagram use and personal involvement.

H1b: Influencer posts with an exact like count display will be perceived to be more credible than influencer posts without a visible like count display when controlling for Instagram use and personal involvement.

H2: Influencer posts with a visible comment count will be perceived to be more credible than influencer posts without a visible comment count when controlling for Instagram use and personal involvement.

The visible like count is manipulated in two ways: an approximated display (i.e., thousands of others like this post) and an exact display (i.e., 4,137 like this post). Previous studies have looked at the effect of exact displays of popularity cues (Engelmann & Wendelin, 2017; Hu, 2013), but have not evaluated approximated displays. However, based on the warranting principle, the value of user-generated engagement as a third-party source decreases when the source is masked (DeAndrea, 2014). The change to an approximated like display may raise concerns about the source

since the exact number of likes is not displayed or verifiable without the dropdown list of everyone who has liked the post. However, this has not been previously tested. Therefore, this research seeks to examine the effect of an approximate display versus an exact display of consensus by posing the following research question:

RQ: Which type of visible like count display (i.e., exact or approximate) generates a higher level of perceived influencer credibility?

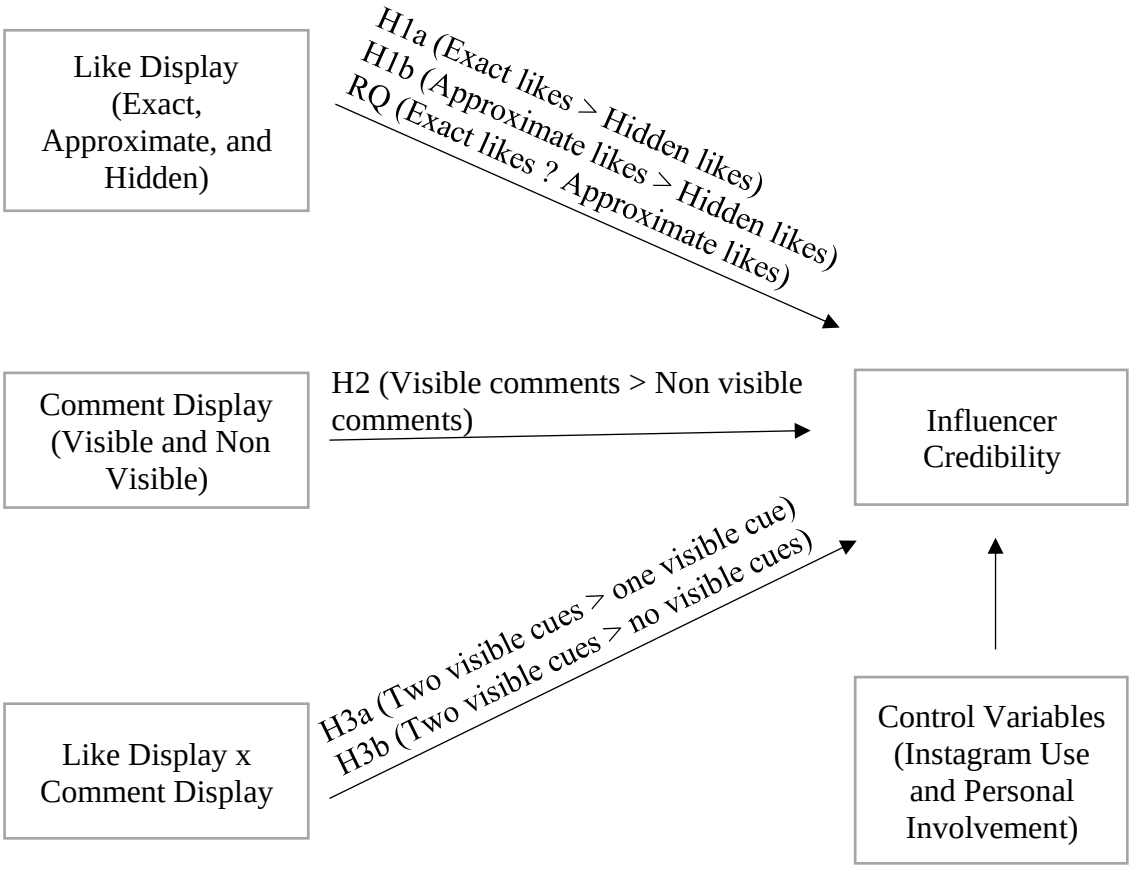
As the warranting principle predicts, the change to a hidden like count display may fundamentally change the way people verify the source of third-party information. Viewers will no longer be able to click on the visible like count and view a list of all users who have liked the particular post. It is hypothesized that by masking the visible like count, the ambiguity around the user-generated likes will lower the warranting value and produce lower source credibility evaluations. Based on the warranting principle, posts that feature two different types of warranting cues (i.e., likes and comments) will give the viewer more third-party information on which to base judgements. The more cues present in the post, the greater the ability the viewer has to determine the reliability of information. As supported by the warranting principle, the higher the perceived warranting value, the greater effect the post will have on impression formation (DeAndrea, 2014). Therefore, the following hypotheses are posed regarding the interaction effect of likes and comments on credibility:

H3a: Influencers whose posts feature two forms of visible cues (i.e., visible like count and comment count) will be perceived to be more credible than an influencer whose posts feature one form of visible cue (i.e., visible like count or comments count when controlling for Instagram use and personal involvement.

H3b: Influencers whose posts feature two forms of visible cues (i.e., visible likes count and comment count) will be perceived to be more credible than an influencer whose posts feature no visible cues (i.e., no like count and no comment count) when controlling for Instagram use and personal involvement.

See Figure 7 for a conceptual model that outlines the aforementioned research question and hypotheses.

Figure 7 Conceptual Model of Heurtisitc Processing of User-Generated Engagmeent Cues on the Explore Page of Instagram



CHAPTER 3. RESEARCH DESIGN

3.1 Research Design

The researcher conducted a 3 (like display: hidden like count, approximated number of likes, and the exact number of likes) x 2 (comment display: hidden comment count and visible comment count) x 2 (influencer type: travel and food) mixed-design online experiment. Participants were exposed to two messages displayed in a random order. The like and comment display are between-subject factors and the influencer type is a within-subjects factor. Each are discussed in more detail below.

3.1.1 Independent Variables

The study manipulated the level of user-generated engagement (i.e., visibility of like counts and visibility of comment counts) presented in each Instagram post (i.e., travel post and food post). See Table 1 for a visual display. Below, the independent variables are described in more detail.

Table 1 Manipulated Independent Variables and Subsequent Conditions

		Influencer Type			
		Travel		**Food**	
		Comment Display			
		Not visible	Visible	Not visible	Visible
Like Display	Hidden	Con 1T	Con 4T	Con 1F	Con 4F
	Approximate	Con 2T	Con 5T	Con 2F	Con 5F
	Exact	Con 3T	Con 6T	Con 3F	Con 6F

Note. The abbreviation "T" represents the travel post and the abbreviation "F" represents the food post.

3.1.1.1 Likes

Likes were manipulated in three ways: hidden like count display, approximated like count display, and exact like count display. The hidden like count display featured the text "Liked by [Instagram friend's name] and others." The approximated like count display featured the text "Liked by [Instagram friend's name] and thousands of others." The exact like count display featured the text "Liked by [Instagram friend's name] and 4,057 others."

3.1.1.2 Comments

Comments were manipulated based on visibility. Within the Explore feature, comments are currently not visible. However, with the removal of a visible like count, making comments visible on the Explore page may be a suitable alternative to help consumers make judgments regarding the credibility of a source. Therefore, this study seeks to manipulate comment visibility in the Instagram post that users click to see on the Explore page. Under the Instagram post's caption, the comment count was either visible and displayed with the message "View all 164 comments" or no comment count was visibly displayed.

3.1.2 Repeated Measure

The effect of user-generated engagement on an individual's perception of a source will depend on the individual's specific attentional processes. What one individual ascribes attention to will depend on the vividness of the cue and the salience (Haim et al., 2018). Visibility of user-generated engagement is being manipulated in this experiment as a between-subjects visible indication of consensus and popularity. However, individual

salience, which is the topic relevance individuals have, may affect their perceptions. To control for individual salience, the researcher used a within-subject variable of influencer type to avoid a single-message design and to enhance the external validity of the experiment. The influencer falls into the categorization of either travel (i.e., itsbaileyw) or food (i.e., arsmith). These two categories were selected as they are popular topics featured on Instagram's Explore page.

3.1.3 Stimuli Message Design

While Instagram has several features where users can view content, to limit the scope of this research, the Explore page was studied within this experiment. Each stimulus was designed to look like a real Instagram post that a user would see scrolling through their feed. Each stimulus has a profile picture that represents the type of influencer without explicitly showing a face. This decision was made in an effort to control for social stereotypes and comparisons to oneself. Similarly, the main image featured in the post is a flat lay of items related to the influencer type. For the food post, the image features a flat lay of baking ingredients. For the travel post, the image features a flat lay of items related to traveling, such as a map, foreign currency, and a passport.

Since this study is purely looking at the effect of user-generated engagement on an influencer's perceived credibility, the stimuli were designed to exclude persuasive intent in the caption. Therefore, the stimuli do not center around a sponsorship of a brand; rather, the stimuli are designed as non-advertising content purely about the influencer's area of specialty (i.e. food or travel). Therefore, ad recognition will not interfere with credibility judgments. While influencers are known for posting persuasive content, the stimuli were specifically designed to minimize persuasion within the caption. By keeping

the caption simple and descriptive, participants can focus on the persuasive nature of the user-generated engagement rather than the caption of the post. The caption for each post is a simple phrase that relates to the influencer's niche: "Creating my next recipe" and "Dreaming of my next trip." Both captions are similar in word count and message form. All images used in the stimuli were curtesy of Pexels (n.d.) and free for use.

3.2 Manipulation Checks

In order to determine the effectiveness of the manipulation, the survey includes two multiple-choice questions designed to determine each participant's awareness regarding their assigned condition. The questions are as follows: "What do you notice about the likes on this post?" and "What do you notice about the comments on this post?" When responding to the question regarding the like display, participants could select one of five options: "I see likes by my friend arsmith [itsbaileyw}and others," "I see likes by my friend arsmith [itsbaileyw] and thousands of others,"" I see likes by my friend arsmith [itsbaileyw} and 4057 of others," "I do not know," or "other." When responding to the question regarding the comment display, participants could select one of four options: "I do not see comments at all," "I see a message of 'view 164 comments'," "I do not know," and "other."

3.2.1 Pretest 1

To pretest the stimuli messages and check if the participants paid attention to the manipulation, 68 undergraduate students from the University of Kentucky participated in an online experiment. Participants were recruited through a convivence sample using the college's research participation system, SONA. Of the 68 participants, 53 (77.90%) were

female, 14 (20.60%) were male, and 1 (1.50%) individual identified as non-binary. Participants ranged in age from 18 to 23 (M = 19.93; SD = 1.08). Fifty-five (80.90 %) participants identified as white, 5 (7.40%) identified as Black or African American, 3 (4.40%) identified as Asian, 2 (2.90%) identified as Hispanic or Latino(a), 2 (2.90%) selected other and clarified that they identified as multi-racial, and 1 (1.50%) preferred not to answer. Participants ranged in education classification level: 25 participants were sophomores (36.80%), 20 (29.40%) were juniors, 15 (22.10%) were freshman, and 8 (11.80%) were seniors. See Table 2 for a visual display of demographic information. Participants were randomly assigned to one of six conditions with a repeated measure. The order of the repeated measure (i.e., influencer type) was randomized. Participants were asked to respond to two multiple-choice questions by identifying the answer that best pertains to what they noticed about the likes and comments, respectively, on the post. Within this round of message testing, the researcher sought to compare how participants perceived the independent variable (i.e. like count and comment count) visibility in relation to the condition that they randomly received.

Table 2 Demographic Profile for Pretest 1

		Count	Percentage
Gender	Male	14	20.60%
	Female	53	77.90%
	Other	1	1.50%
Age	18	4	5.90%
	19	22	32.40%
	20	23	33.80%
	21	15	22.10%
	22	2	2.90%
	23	2	2.90%
	24	0	0%
	25	0	0%
	26	0	0%
Education	Freshman	15	22.10%
	Sophomore	25	36.80%
	Junior	20	29.40%
	Senior	8	11.80%
Ethnicity/Race	American Indian or Native	0	0%
	Asian	3	4.40%
	Black or African	5	7.40%
	American	2	2.90%
	Hispanic or Latino(a)	55	80.90%
	White	2	2.90%
	Other	1	1.50%
	Prefer Not to Answer		

3.2.1.1 Manipulation Check of Likes for Pretest 1

A cross-tabulation analysis was conducted to discover if there is a relationship between the randomly assigned condition and the observed frequencies for the participant's response to "What do you notice about the likes on this post?" (See Table 3). The chi-square test for independence indicated a significant association between the assigned condition and perceived like display when viewing the travel influencer's post, x^2 (6, 68) = 66.42, $p < .001$, and when viewing the food influencer's post, x^2 (6, 68) = 92.70, $p < .001$.

Table 3 Cross-tabulation of Likes for Pretest 1

			What do you notice about the likes on this post? –				
			I do not see likes at all	**I see likes by my friend @arsmith [@itsbaileyw] and others**	**I see likes by my friend @arsmith [@itsbaileyw] and thousands of others**	**I see likes by my friend @arsmith [@itsbaileyw] and 4057 others**	**Total**
Like Condition for Influencer Message Type of Travel	**No Visibility**	Count	2	19	0	1	22
		% within Like Condition	9.10%	86.40%	0.00%	4.50%	100%
	Approx.	Count	0	5	18	0	23
		% within Like Condition	0.00%	21.7%	78.3%	0.00%	100%
	Exact	Count	0	3	6	14	23
		% within Like Condition	0.00%	13.00%	26.10%	60.9%	100%
Like Condition for Influencer Message Type of Food	**No Visibility**	Count	1	21	0	0	22
		% within Like Condition	4.50%	95.50%	0.00%	0.00%	100%
	Approx.	Count	0	2	20	1	23
		% within Like Condition	0.00%	8.70%	87.00%	4.30%	100%
	Exact	Count	1	0	5	17	23
		% within Like Condition	4.3%	0.00%	21.70%	73.90%	100%

Table 4 Chi-Square Test for Travel Post Likes For Pretest 1

	Value	*df*	*Asymptotic Significance (2-sided)*
Pearson Chi-Square	*66.42[a]*	*6*	*.000*
Likelihood Ratio	*71.64*	*6*	*.000*
Linear-by-Linear Association	*35.58*	*1*	*.000*
N of Valid Cases	*68*		

a. 4 cells (33.3%) have expected count less than 5. The minimum expected count is .65.

Table 5 Chi-Square Test for Food Post Likes For Pretest 1

	Value	*df*	*Asymptotic Significance (2-sided)*
Pearson Chi-Square	*92.70[a]*	*6*	*.000*
Likelihood Ratio	*100.28*	*6*	*.000*
Linear-by-Linear Association	*45.30*	*1*	*.000*
N of Valid Cases	*68*		

a. 3 cells (25.0%) have expected count less than 5. The minimum expected count is .65.

Z-tests were then conducted to compare column proportions between the assigned condition and the perceived like display. For the travel influencer message, 19 (86.40%) participants in the non-visible likes condition correctly reported that they saw "likes by my friend @arsmith [@itsbaileyw] and others," which was significantly more than the 3 (13.60%) participants who reported incorrectly, $z = 4.82$, $p < .001$. For the food influencer's post, 21 (95.50%) participants correctly identified the non-visible likes condition, significantly more than the one person (4.50%) who incorrectly identified the non-visible condition, $z = 6.03$, $p < .001$. Therefore, the non-visible like condition for both the travel and food message produced a significant difference, which means that the manipulation of the non-visible like condition was successful.

For participants in the approximate like condition viewing the travel post, 18 (78.30%) participants correctly answered the manipulation check question, which was

significantly more than the 5 (21.70%) participants who incorrectly identified the approximate like condition, $z = 3.83$, $p < .001$. For participants in the approximate like condition viewing the food post, 20 (87.00%) participants correctly identified the approximate like condition, which are significantly more than the 3 (13.00%) participants who incorrectly identified the approximate like condition, $z = 5.01$, $p < .0001$. Therefore, the manipulation of the approximate like condition for both the travel and food post was successful.

For those in the exact like condition viewing the travel post, 14 (60.9%) participants correctly identified the exact like condition, which was not significantly different from the 9 (39.10%) participants who answered incorrectly, $z = 1.47$, $p = .14$. Also, for those in the exact like condition viewing the food post, 17 (73.90%) participants in the exact like condition correctly identified the exact like condition, which was significantly more than the 6 (26.00%) participants who incorrectly identified the exact like condition, $z = 3.24$, $p = .0012$. Therefore, the manipulation of the exact like condition was successful for the food influencer's post but not for the travel influencer's post.

3.2.1.2 Manipulation Check of Comments for Pretest 1

A cross-tabulation analysis was conducted to discover if there is a relationship between the randomly assigned condition and the observed frequencies for the participant's response to "What do you notice about the comments on this post?" (See Table 4). A chi-square test for independence indicated a significant association between the assigned condition and perceived comment display when viewing the travel influencer influencer's post, $x^2 (4, 68) = 37.14$, $p < .001$ and when viewing the food influencer's post, $x^2 (3, 68) = 27.24$, $p < .001$.

Table 6 Cross-tabulation of Comments for Pretest 1

			What do you notice about the comments on this post?					
			I do not see comments at all	**I see [Influencer's name] comment**	**I see [Influencer's name] comment and a message to view 164 comments**	**I do not know**	**Other**	**Total**
Comment Condition for Influencer Message Type of Travel	**No Visibility**	Count	21	14	0	0	0	35
		% within Like Condition	60.00%	40.00%	0.00%	0.00%	0.00%	100%
	Visibility	Count	10	1	20	1	1	33
		% within Like Condition	30.30%	3.03%	60.60%	3.03%	3.03%	100%
Comment Condition for Influencer Message Type of Food	**No Visibility**	Count	28	7	0	0	0	35
		% within Like Condition	80.00%	20.00%	0.00%	0.00%	0.00%	100%
	Visibility	Count	16	0	12	0	5	33
		% within Like Condition	48.50%	0.00%	36.40%	0.00%	7.40%	100%

Table 7 Chi-Square Test for Travel Post Comments for Pretest 1

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	37.14[a]	4	.000
Likelihood Ratio	47.88	4	.000
Linear-by-Linear Association	19.94	1	.000
N of Valid Cases	68		

a. 4 cells (40.00%) have expected count less than 5. The minimum expected count is .49.

Table 8 Chi-Square Test for Food Post Comments for Pretest 1

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	27.24[a]	3	.000
Likelihood Ratio	36.53	3	.000
Linear-by-Linear Association	15.11	1	.000
N of Valid Cases	68		

a. 4 cells (50.00%) have expected count less than 5. The minimum expected count is 2.43.

Tests of proportions were then conducted to compare column proportions between the assigned condition and the perceived comment display. For participants in the non-visible comment condition viewing the travel influencer's post, 21 (60.00%) participants correctly identified the non-visible comment condition, which was not significantly more than the 14 (40.00%) participants who incorrectly identified the non-visible comment condition, $z = 1.67$, $p = .09$. Thus, the manipulation of the non-visible comment condition for the travel message was not successful.

For participants in the non-visible comment condition viewing the food influencer's post, 28 (80.00%) participants correctly identified the non-visible comment condition, which was significantly more than the 7 (20.00%) participants who incorrectly identified the non-visible comment condition, $z = 5.02$, $p < .001$. Therefore, the manipulation of the non-visible comment condition for the food message was successful.

For participants in the visible comment condition viewing the travel post, 20 (60.60%) participants correctly identified the visible comment condition, which was not significantly more than the 13 (39.39%) participants who incorrectly identified the visible comment condition, $z = 1.72$, $p = .09$. Therefore, the manipulation of the visible comment condition for the travel post was not successful.

For participants in the visible comment condition viewing the food post, 12 (36.40%) participants correctly identified the visible comment condition, which was significantly fewer than those 21 (55.9%) participants who incorrectly identified the visible comment condition, $z = -2.22$, $p < .05$. Therefore, the manipulation of the visible comment condition for the food post was not successful.

It is clear that many participants did not feel that the comment left by the influencer should be a comment. It can be assumed that they viewed the message posted by the influencer as a photo caption and define messages from individuals other than the initial message left by the influencer as comments. Therefore, the multiple-choice option of " I see [influencer's name]'s comment" was deleted, and the response of "I see [influencer's name]'s comment and a message to view 164 comments" was replaced with "I see a message of 'view 164 comments.'" The effectiveness of this change was evaluated in a second pretest.

3.2.2 Pretest 2

To further verify the manipulation check, the researcher employed a second pretest. Sixty-eight undergraduate students from the University of Kentucky participated in the second pretest. Like the first pretest, participants were recruited through a convivence sample using the college's research participation system, SONA. Of the 84 participants, 54 (64.3%) were female and 30 (35.70%) were male. Participants ranged in age from 18 to 25 (M = 19.94; SD = 1.36). Sixty-five (77.40 %) participants identified as white, 7 (8.30%) identified as Black or African American, 5 (6.00%) selected other and clarified that they identified as multi-racial, 3 (3.60%) identified as Asian, 3 (3.60%) identified as Hispanic or Latino(a), and 1 (1.2%) preferred not to answer. Participants also ranged in classification level: 29 (34.5%) were juniors, 26 (31.00%) participants were freshmen, 18 (21.40%) were sophomores, and 11 (13.1%) were seniors. See Table 5 for a visual representation of the demographic information. The second pretest had the same procedures and measure as the first one expect for the revised manipulation check questions.

Table 9 Demographic Profile for Pretest 2

		Count	Percentage
Gender	Male	30	35.7%
	Female	54	64.3%
	Other	0	0%
Age	18	14	16.70%
	19	18	21.40%
	20	23	27.40%
	21	21	25.00%
	22	6	7.10%
	23	1	1.20%
	24	0	0%
	25	1	1.20%
	26	0	0%
Education	Freshman	26	31.00%
	Sophomore	18	21.40%
	Junior	29	34.50%
	Senior	11	13.10%
Ethnicity/Race	American Indian or Native	0	0%
	Asian	3	3.60%
	Black or African American	7	8.30%
	Hispanic or Latino(a)	3	3.60%
	White	65	77.4%
	Other	5	6.00%
	Prefer Not to Answer	1	1.20%

3.2.2.1 Manipulation Check of Likes for Pretest 2

A cross-tabulation analysis was conducted to discover if there is a relationship between the randomly assigned condition and the observed frequencies for the participant's response to "What do you notice about the likes on this post?" (See Table 6). The chi-square test for independence indicated a significant association between the assigned condition and perceived like display when viewing the travel influencer's post, x^2 (10, 84) = 90.01, $p < .001$ and when viewing the food influencer's post, z^2 (8, 84) = 80.61, $p < .001$. However, there did seem to be some confusion among participants regarding the difference between the like manipulations. Therefore, Z-scores were

calculated to compare column proportions between the assigned condition and the perceived comment display.

Table 10 Cross-tabulation for Likes for Pretest 2

			What do you notice about the likes on this post?						
			I do not see likes at all	**I see likes by my friend arsmith [itsbaileyw] and others**	**I see likes by my friend arsmith [itsbaileyw] and thousands of others**	**I see likes by my friend arsmith [itsbaileyw] and 4057 others**	**I don't know**	**Other**	**Total**
Like Condition for Influencer Message Type of Travel	**No Visibility**	Count	2	28	0	0	0	0	30
		% within Like Condition	6.70%	93.3%	0.00%	0.00%	0.00%	0.00%	100%
	Approx.	Count	0	6	19	1	1	0	27
		% within Like Condition	0.00%	22.20%	70.37%	3.70%	3.70%	0.00%	100%
	Exact	Count	0	4	5	17	0	1	27
		% within Like Condition	0.00%	14.80%	18.50%	63.00%	0.00%	3.70%	100%
Like Condition for Influencer Message Type of Food	**No Visibility**	Count	3	25	0	1	1	0	30
		% within Like Condition	10.00%	83.33%	0.00%	3.33%	3.33%	0.00%	100%
	Approx.	Count	0	6	20	0	1	0	27
		% within Like Condition	0.00%	22.20%	74.10%	0.00%	3.70%	0.00%	100%
	Exact	Count	0	6	5	16	0	0	27
		% within Like Condition	0.00%	22.20%	18.50%	59.30%	0.00%	0.00%	100%

Table 11 Chi-Square Test for Travel Post Likes for Pretest 2

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	90.01[a]	10	.000
Likelihood Ratio	94.81	10	.000
Linear-by-Linear Association	44.94	1	.000
N of Valid Cases	84		

a. 9 cells (50.0%) have expected count less than 5. The minimum expected count is .32.

Table 12 Chi-Square Test for Food Post Likes for Pretest 2

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	80.61[a]	8	.000
Likelihood Ratio	85.69	8	.000
Linear-by-Linear Association	29.61	1	.000
N of Valid Cases	84		

a. 6 cells (40.0%) have expected count less than 5. The minimum expected count is .64.

For participants in the non-visible like condition viewing the travel influencer's post, 28 (93.30%) participants correctly identified the non-visible like condition, which was significantly more than the 2 (6.70%) participants who incorrectly identified the non-visible like condition, $z = 6.71$, $p < .001$. For participants in the non-visible like condition viewing the food influencer's post, 25 (83.33%) correctly identified the non-visible like

condition, which was significantly more than the 5 (16.66%) participants who incorrectly identified the non-visible like condition, z =5.16, $p < .001$. Therefore, the manipulation of the non-visible likes condition was successful for both the travel and the food influencer's post.

For those in the approximate like condition viewing the travel influencer's post, 19 (70.37%) participants correctly identified the approximate like condition, which was significantly more than the 6 (29.60%) participants who incorrectly identified the approximate like condition, $z = 2.99$, $p = .003$. For those in the approximate like condition viewing the food influencer's post, 20 (74.10%) participants correctly identified the approximate like condition, which was significantly more than the 7 (25.90%) participants who incorrectly identified the approximate like condition, $z = 3.54$, $p < .001$. Thus, the manipulation of the approximate like condition was successful for both the travel and food influencer's posts.

For participants in the exact like condition viewing the trave post, 17 (63.00%) participants correctly identified the exact like condition, which was only marginally significantly more than the 10 (37.00%) participants who incorrectly identified the exact like condition, $z = 1.91$, $p = .06$. For those in the exact like condition viewing the food post, 16 (59.30%) participants correctly identified the exact like condition, which was only marginally significantly more than the 11 (40.70%) participants who incorrectly identified the exact like condition, $z = 1.91$, $p = .056$. Therefore, the manipulation of the exact like condition was not successful. This pretest results showed that participants struggled to tell the difference between the three types of like displays. To reduce this confusion, the question was reworded to "What do you notice about the like display on

this post?" This addition of "display" was meant to bring more awareness to the specific presentation of the likes, rather than just to the general presence of a like display. Additionally, the answer choice of "I do not see likes" was removed.

3.2.2.2 Manipulation Check of Comments for Pretest 2

A cross-tabulation analysis was conducted to discover if there is a relationship between the randomly assigned condition and the observed frequencies for the participant's response to "What do you notice about the comments on this post?" (See Table 7). A chi-square test for independence indicated a significant association between the assigned condition and perceived comment display when viewing the travel influencer post, x^2 (3, 84) = 67.5, $p < .001$ and when viewing the food influencer post, x^2 (2, 84) = 66.78, $p < .001$.

Table 13 Cross-tabulation of Comments for Pretest 2

			What do you notice about the comments on this post?				
			I do not see comments at all	**I see [Influencer's] comment and a message to view 164 comments**	**I do not know**	**Other**	**Total**
Comment Condition For Influencer Message Type of Travel	**No Visible Comments**	Count	40	0	1	1	42
		% within Comment Condition	95.20%	0.00%	2.40%	2.40%	100%
	Visible Comments	Count	4	37	1	0	42
		% within Comment Condition	9.50%	88.1%	2.40%	0.00%	100%
Comment Condition For Influencer Message Type of Food	**No Visible Comments**	Count	39	2	1	0	42
		% within Comment Condition	92.90%	4.80%	2.40%	0.00%	100%
	Visible Comments	Count	2	39	1	0	42
		% within Comment Condition	4.80%	92.90%	2.40%	0.00%	100%

Table 14 Chi-Square Test for Travel Post Comments for Pretest 2

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	67.50[a]	3	.000
Likelihood Ratio	86.87	3	.000
Linear-by-Linear Association	36.90	1	.000
N of Valid Cases	84		

a. 4 cells (50.00%) have expected count less than 5. The minimum expected count is .50.

Table 15 Chi-Square Test for Food Post Comments for Pretest 2

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	66.78[a]	2	.000
Likelihood Ratio	81.71	2	.000
Linear-by-Linear Association	54.34	1	.000
N of Valid Cases	84		

a. 2 cells (33.30%) have expected count less than 5. The minimum expected count is 1.00.

Z-tests were then conducted to compare column proportions between the assigned condition and the perceived comment display. For participants in the non-visible comment condition viewing the travel post, 40 (95.20%) participants correctly identified the non-visible comment condition, which was significantly more than the 2 (4.80%) participants who incorrectly identified the non-visible comment condition, $z = 8.29$, $p < .001$. For those in the non-visible comment condition viewing the food post, 39 (92.90%)

correctly identified the non-visible comment condition, which was significantly more than the 3 (7.20%) participants who incorrectly identified the non-visible comment condition, $z = 7.86$, $p < .001$. Therefore, the manipulation of the non-visible like condition was successful for both the travel and food posts.

For participants in the visible comment condition viewing the travel post, 37 (88.10%) participants correctly identified the visible comment condition, which was significantly more than the 5 (11.90%) participants who incorrectly identified the visible comment condition, $z = 6.98$, $p < .001$. For those in the visible comment condition viewing the food post, 39 (92.90%) participants correctly identified the visible comment condition, which was significantly more than the 3 (7.20%) participants who incorrectly identified the visible comment condition, $z = 7.89$, $p < .001$. Therefore, the manipulation of the visible comment condition was successful for both the travel and food posts. The changes in the wording of the answer choices from pretest 1 to pretest 2 successfully reduced confusion regarding the comment condition.

3.3 Main Study Participants

A purposive convenience sample of undergraduate students (N= 336) was recruited from undergraduate communication courses at a large university in the southeastern United States. Participants were gathered through the university's participant management software known as SONA. As an incentive, participants could fulfill course credit by engaging in the study. Participation was restricted to individuals between the ages of 18 and 26 and those who had an Instagram account. A priori power analysis with G*Power found that for a within-subjects design, 246 people were needed for a .95 power to detect a small effect. A total of 336 people participated in the study. However, two

participants did not complete the survey, and six participants were excluded due to selecting the wrong choice on an attention check question. This left a final sample size of 328 .

3.3.1 Demographics

Of the 328 participants, 168 (51.2%) were female and 158 (48.2%) were male. Participants ranged in age from 18 to 26 (M = 20.05; SD = 1.40). Three (.90%) participants identified as Asian, 1 (.30%) identified as American Indian or Alaska Native, 40 (12.20%) identified by Black or African American, 11 (3.40%) identified as Hispanic or Latino(a), 255 (77.70%) identified as White, 12 (3.70%) identified as mixed race, 3 (.90%) selected other, and 3 (.90%) preferred not to answer. Participants also ranged in classification level: 93 (28.40%) were freshman, 107 (32.60%%) were sophomores, 77 (23.5%) were juniors, and 51 (15.50%) were seniors. See Table 8 for the detailed demographic profiles.

Table 16 Demographic Profile for Main Study

		Count	Percentage
Gender	Male	158	48.20%
	Female	168	51.20%
	Other	1	.30%
	Prefer Not to Answer	1	.30%
Age	18	32	9.80%
	19	100	30.50%
	20	88	26.80%
	21	61	18.60%
	22	30	9.10%
	23	10	3.00%
	24	5	1.50%
	25	1	.30%
	26	1	.30%
Education	Freshman	93	28.40%
	Sophomore	107	32.60%
	Junior	77	23.50%
	Senior	51	15.50%
Ethnicity/Race	American Indian or Native	1	.03%
	Asian	3	.09%
	Black or African American	40	12.20%
	Hispanic or Latino(a)	11	3.40%
	White	255	77.70%
	Mixed Race	12	37.70%
	Other	3	.09%
	Prefer Not to Answer	3	.09%

3.4 Procedure and Data Collection

Once IRB approval from the university's Office of Research Integrity was obtained, the researcher began recruiting participants through the university's participant pool. Participants self-selected into the study at their convivence. Participants engaged in the study digitally via a device that could connect to the internet (i.e., desktop, laptop, mobile device). Once a participant signed up for the study, they were redirected to an online questionnaire that was administered via Qualtrics. The consent form was presented to participants as a cover letter at the beginning of the survey. Once the consent form was

reviewed, participants clicked “yes” to indicate that they consented to participate in the study and clicked “no” to indicate that they did not consent to participate. Those who selected yes, were redirected to screener questions. Participants that selected “no” were redirected to the end of the survey. Participants then answered two screener questions to verify their eligibility for the study. If the participant answered that they were between the ages of 18 and 26 and had an active Instagram account, they were redirected to the beginning of the survey and randomly assigned to one of six conditions. The system was set up to randomly select which message type would be displayed to the participant first.

In the travel [food] influencer condition, participants were instructed to imagine that they had opened Instagram and had decided to click on the magnifying glass icon in order to go to the Explore page to discover new content from accounts they do not follow yet. They were instructed to imagine that they selected the travel [food] icon from a list of curated topics at the top of the Explore page. Participants were then shown an image of what the hypothetically populated Explore page would look like to help them imagine the scenario. The participant was then instructed to imagine that they had clicked on the top left photo populated on the Explore page to get a better view of the singular post. Once viewing the post, participants were instructed to imagine that they had a friend named Adrian Smith [Bailey Williams] better known by their username @arsmith [@itsbaileyw].

After viewing the image, participants were asked to click on the parts of the post that stood out to them as most important. Participants were then asked to respond to two multiple-choice manipulation check questions regarding what they noticed about the likes and comments: “What did you notice about the likes on this post?” and “What did you

notice about the comments on this post?" After stimulus exposure, participants were asked to indicate their perception of the source by selecting the option that most closely aligns with their reaction to the Instagram influencer on a 10 item, seven-point bipolar scale and indicate their personal involvement with the post by reflecting on their feelings and selecting the option that most closely aligns with their thoughts on a 10 item, seven-point bipolar scale. Participants repeated answering these questions twice, once for each influencer type.

The survey questionnaire ends by asking participants to respond to questions that pertain to demographics and Instagram use. Participants were asked to indicate their age, gender, racial/ethnic background, college classification level. Additionally, participants were asked to indicate how often they check Instagram per day and how much time they spend on Instagram per day. Participants had the option to leave feedback at the end of the survey.

The Qualtrics survey took participants approximately 5 minutes to complete. Participants were awarded SONA credit in their classes based on the completion of the study. All participation took place outside of regular class time, and participants completed the questionnaire anonymously.

3.4.1 Measures

3.4.1.1 Dependent Variable

3.4.1.1.1 Source Credibility

Source credibility (Cronbach α = .92 for the travel influencer, Cronbach α = .93 for the food influencer) was measured through the two subscales on Ohanian's (1990) source

credibility scale. While this scale was originally used to measure the expertise, trustworthiness, and attractiveness of celebrity endorsers, this scale is ideal for a multitude of consumer behavior research (Bearden, Netemeyer, & Haws, 2011). Within this study, the scale will be used to evaluate social media influencers who function similarly to celebrity endorsers. This study utilized the two dimensions of source credibility: trustworthiness and expertise. 1) Trustworthiness was measured with five bipolar items, e.g., dependable—undependable, honest—dishonest, reliable—unreliable, sincere—insincere, trustworthy, untrustworthy. 2) Expertise was measured with five bipolar items, e.g., expert—not an expert, experienced—inexperienced, knowledgeable—unknowledgeable, qualified—unqualified, skilled—unskilled.

3.4.1.2 Covariates

3.4.1.2.1 INSTAGRAM USE

Instagram use was measured by using the Social Networking Site Usage & Needs Scale (Ali et al., 2020), adapted to focus solely on Instagram usage. The following questions were asked: "How often do you check Instagram per day" and "How much time do you spend on Instagram per day?" Participants could select from one of the following answers when responding to how often they check Instagram: on every notification beep, 1-2 times per day, 3-4 times per day, 5-6 times per day, 7-8 times per day, 9+ times per day, and other. When responding to the question regarding how much time they spend on Instagram per day, participants could select one of the following options: less than 15 minutes, 30 minutes to 1 hour, 1-2 hours, 3-4 hours, 5-6 hours, 7-8 hours, 9+ hours, and other. If a participant selected other, they were asked to please specify how often they check Instagram.

3.4.1.2.2 PERSONAL INVOLVEMENT INVENTORY

Personal involvement is important to study within consumer research due to its implications on the heuristics systematic model. The heuristic systematic model states that the message process is affected by the amount of issue-relevant elaboration an individual engages in (Sengupta et al., 1997). Thus, someone high in involvement will be more likely to engage in the systematic route rather than the heuristics route. Therefore, it is important to measure and control for the effects of participant's personal involvement with the topic of the Instagram post. Participants were asked to respond to the Revised Personal Involvement Inventory (Cronbach $\alpha = .92$ for the travel post, Cronbach $\alpha = .93$ for the food post), with ten bipolar items on a 7-point scale: important/unimportant, boring/interesting, relevant/irrelevant, exciting/unexciting, means nothing/means a lot to me, appealing/unappealing, fascinating/mundane, worthless/valuable, involving/uninvolving, and not needed/needed (Zaichkowsky, 1994). See Table 9 for a list of measures.

Table 17 Table of Measurements

Constructs	Item	Source	Cronbach's α
Source Credibility	Please indicate your perception of the source by selecting the option that mostly closely aligns with your reaction to the Instagram influencer.	(Ohanian, 1990)	.92 for travel; .93 for food
Instagram Use	How often do you check Instagram per day? How much time do you spend on Instagram per day?	(Ali et al., 2020)	
Personal Involvement Inventory	After viewing the post, please indicate your feelings regarding the post by selecting the option that most closely aligns with your thoughts.	(Zaichkowsky, 1994)	.92 for travel; .93 for food

CHAPTER 4. RESULTS

4.1 Manipulation Check

A cross-tabulation analysis was conducted to discover if there is a relationship between the randomly assigned condition and the observed frequencies for the participant's response to "What do you notice about the comments on this post?" (See Table 10). The chi-square test for independence indicated a significant association between the assigned condition and perceived like display when viewing the travel influencer's post, x^2 (8, 328) = 268.13, $p < .001$ and when viewing the food influencer's post, x^2 (8, 328) = 259.99, $p < .001$.

Table 18 Cross-tabulation of Likes for Main Study

			What do you notice about the likes on this post?					
			I see likes by my friend arsmith [itsbaileyw] and others	**I see likes by my friend arsmith [itsbaileyw] and thousands of others**	**I see likes by my friend arsmith [itsbaileyw] and 4057 others**	**I don't know**	**Other**	**Total**
Like Condition for Influencer Message Type of Travel	**No Visibility**	Count	99	2	3	5	1	110
		% within Like Condition	90.00%	1.80%	2.70%	4.50%	0.90%	100%
	Approx.	Count	23	79	4	2	2	110
		% within Like Condition	20.90%	71.80%	3.60%	1.80%	1.80%	100%
	Exact	Count	24	19	56	4	5	108
		% within Like Condition	22.20%	17.60%	51.90%	3.70%	4.60%	100%
Like Condition for Influencer Message Type of Food	**No Visibility**	Count	100	3	1	4	2	110
		% within Like Condition	90.90%	2.70%	.90%	3.60%	1.80%	100%
	Approx.	Count	23	80	2	3	2	110
		% within Like Condition	20.90%	72.70%	1.80%	2.70%	1.8%	100%
	Exact	Count	34	17	52	3	2	108
		% within Like Condition	31.50%	15.70%	48.10%	2.80%	1.90%	100%

Table 19 Chi-Square Test for Travel Post Likes for Main Study

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	268.13[a]	8	.000
Likelihood Ratio	265.35	8	.000
Linear-by-Linear Association	88.75	1	.000
N of Valid Cases	328		

a. 6 cells (40.0%) have expected count less than 5. The minimum expected count is 2.63.

Table 20 Chi-Square Test for Food Post Likes for Main Study

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	259.99a	8	.000
Likelihood Ratio	259.01	8	.000
Linear-by-Linear Association	67.13	1	.000
N of Valid Cases	328		

a. 6 cells (40.00%) have expected count less than 5. The minimum expected count is 1.98.

Test of proportions were then conducted to compare column proportions between the assigned condition and the perceived like display. For participants in the non-visible likes condition viewing the travel post, 99 (90.00%) of participants correctly identified the non-visible like condition, which was significantly more than the 11 (9.90%) participants who incorrectly identified the non-visible like display, $z = 11.87$, $p < .001$.

For those in the non-visible like condition viewing the food post, 100 (90.90%) of participants correctly identified the non-visible like condition, which was significantly more than the 10 (9.00%) participants who incorrectly identified the non-visible like display, $z = 12.14$, $p < .001$. Therefore, the manipulation of the non-visible like condition was successful for both the travel and food posts.

For participants in the approximate like condition viewing the travel post, 79 (71.80 %) participants correctly identified the approximate like display, which was significantly more than 31 (28.10%) participants who incorrectly identified the approximate like display, $z = 6.47$, $p < .001$. For those in the approximate like condition viewing the food post, 80 (72.70%) of participants correctly identified the approximate like display, which was significantly more than the 30 (27.20%) participants who incorrectly identified the approximate like display, $z = 6.74$, $p < .00001$. Therefore, the manipulation of the approximate like condition was successful for both the travel and food influencer's posts.

For participants in the exact like condition viewing the travel post, 56 (51.9%) participants correctly identified the exact like condition, which was not significantly more than the 52 (48.1%) participants who incorrectly identified the exact like condition, $z = 0.54$, $p = .59$. For those in the exact like condition viewing the food post, 52 (48.10%) participants correctly identified the exact like display, not significantly more than the 56 (51.90%) participants who incorrectly identified the exact like display, $z = -0.54$, $p = .59$. Therefore, the manipulation of the exact like condition was not successful for both the travel and the food influencer's post.

A cross-tabulation analysis was conducted to discover if there is a relationship between the randomly assigned condition and the observed frequencies for the participant's response to "What do you notice about the comments on this post?" (See Table 11). A chi-square test for independence indicated a significant association between the assigned condition and perceived comment display when viewing the travel influencer's post, x^2 (3, 328) = 257.39, $p < .001$ and when viewing the food influencer's post, x^2 (3, 328) = 241.62, $p < .001$.

Table 21 Cross-tabulation of Comments for Main Study

			What do you notice about the comment display on this post?				
			I do not see comments at all	**I see [Influencer's] comment and a message to view 164 comments**	**I do not know**	**Other**	**Total**
Comment Condition For Influencer Message Type of Travel	**No Visible Comments**	Count	154	6	3	1	164
		% within Comment Condition	93.90%	3.70%	1.80%	.60%	100 %
	Visible Comments	Count	12	151	1	0	164
		% within Comment Condition	7.3%	96.20%	25.00%	0.00%	100 %
Comment Condition For Influencer Message Type of Food	**No Visible Comments**	Count	150	8	3	3	164
		% within Comment Condition	91.50%	4.90%	1.80%	1.80%	100 %
	Visible Comments	Count	14	148	2	0	164
		% within Comment Condition	8.50%	90.20%	1.20%	0.00%	100 %

Table 22 Chi-Square Test for Travel Post Comments for Main Study

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	257.39[a]	3	.000
Likelihood Ratio	313.10	3	.000
Linear-by-Linear Association	197.87	1	.000
N of Valid Cases	328		

a. 4 cells (50.00%) have expected count less than 5. The minimum expected count is .50.

Table 23 Chi-Square Test for Food Post Comments for Main Study

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	241.62[a]	3	.000
Likelihood Ratio	289.19	3	.000
Linear-by-Linear Association	151.33	1	.000
N of Valid Cases	328		

a. 4 cells (50.00%) have expected count less than 5. The minimum expected count is 1.50.

Test of proportions were then conducted to compare column proportions between the assigned condition and the perceived comment display. For participants in the non-visible comment condition viewing the travel post, 154 (93.9%) participants correctly identified the non-visible common condition, which was significantly more than the 10 (6.10%) participants who incorrectly identified the non-visible comment condition, $z = 15.90$, $p < .001$. For those in the non-visible comment condition viewing the food post,

151 (92.10%) participants correctly identified the non-visible common condition, which was significantly more than the 13 (7.90%) participants who incorrectly identified the non-visible comment condition, $z = 15.24$, $p < .001$. Therefore, the manipulation of the non-visible comment condition was successful for both the travel and food post.

For participants in the visible comment condition viewing the travel post, 150 (91.50%) participants correctly identified the visible comment condition, significantly more than the 14 (8.50%) participants who incorrectly identified the visible comment condition, $z = 15.02$, $p < .001$. For those in the visible comment condition viewing the food post, 148 (90.20%) participants correctly identified the visible comment condition, significantly more than the 16 (9.70%) participants who incorrectly identified the visible comment condition, $z = 14.58$, $p < .00001$. Thus, the manipulation of visible comments was successful for both the travel and food posts.

4.2 Test of Research Question

The research question sought to explore which type of visible like count display (i.e., approximate and exact) generates the highest level of source credibility perceptions. Two sets of independent samples t-tests were conducted, one for the travel influencer and the other for the food influencer. Results showed that there was no significant difference in source credibility perceptions for approximate likes ($M = 3.90$, $SD = .88$) and exact likes ($M = 3.92$, $SD = 1.01$) of the travel influencer message; t (216) = -.172, $p = .63$. Similarly, there was no significant difference in source credibility perceptions for approximate likes ($M = 4.05$, $SD = 1.01$) and exact likes ($M = 4.02$, $SD = 1.00$) of the food influencer message; t (216) = .24, $p = .91$. Therefore, there is no significant

difference between the approximate like count display and the exact like count display on source credibility perceptions of either the travel or food influencer's post.

4.3 Test of Hypotheses

To test H1a, H1b, H2, H3a and H3b, two sets of two-way analysis of covariances (ANCOVAs) were used to examine the interaction effect of the likes and comments display on participants' source credibility perceptions of influencers when controlling for Instagram use and personal involvement. This test allows a researcher to compare categorical independent variables (i.e., like condition) and one continuous dependent variable (i.e., source credibility perception) while controlling for one or more covariates (Pallant, 2016). The independent variables were visibility of user-generated engagement in the forms of likes (i.e., non-visible, approximate, and exact) and comments (i.e., non-visible comments and visible comments). The dependent variable consisted of the scores on the source credibility scale. Participants' scores on the personal involvement and Instagram use scales were used as the covariates in this analysis.

Frequency of Instagram use did not have a significant effect on source credibility for the travel condition (F (1, 319) = .27, p = .61) or the food condition (F (1, 319) = .30, p = .59). (See Table 12 and Figure 8 for the ANCOVA results for the influencer message type of travel and Table 13 and Figure 9 for the ANCOVA results for the influencer message type of food). Further, time on Instagram did have a significant effect on source credibility for the travel condition: F (1, 319) = 4.89, p = .03, but did not have a significant effect on source credibility for the food condition: F (1, 319) = .66, p = .42. Personal involvement had a significant effect on source credibility for the travel condition (F (1, 319) = 251.11, $p < .001$), and the food condition (F (1, 319) = 168.83, $p < .001$).

Table 24 ANCOVA Results for the Travel Post

Between-Subjects Factors

		Value Label	N
Like Condition	.00	No Visible Likes	110
	1.00	Approximate Likes	110
	2.00	Exact Likes	108
Comment Condition	.00	Non-visible comments	164
	1.00	Visible Comments	164

Descriptive Statics

Dependent Variable: Source Credibility for Travel Influencer

Like Condition	Comment Condition	Mean	Std. Deviation	N
Non-visible likes	**Non-visible comments**	3.84	1.01	55
	Visible Comments	3.99	.87	55
	Total	3.91	.94	110
Approximate Likes	**Non-visible comments**	3.89	.94	55
	Visible Comments	3.91	.83	55
	Total	3.90	.88	110
Exact Likes	**Non-visible comments**	3.73	1.06	54
	Visible Comments	4.11	.94	54
	Total	3.92	1.01	108
Total	**Non-visible comments**	3.82	1.00	164
	Visible Comments	4.00	8.78	164
	Total	3.91	.94	328

Test of Between-Subjects Effects

Dependent Variable: Source Credibility for Travel Influencer						
Source	**Type III Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**	**Partial Eta Square**
Corrected Model	130.98[a]	8	16.37	32.52	.00	.45
Intercept	24.58	1	24.58	48.83	.00	.13
Frequency	.14	1	.14	.27	.61	.00
Time	2.46	1	2.46	4.89	.03	.02
Personal Involvement Travel	126.42	1	126.42	251.11	.00	.44
Like Condition	.66	2	.33	.66	.52	.00
Comment Condition	.03	1	.03	.07	.80	.00
Like Condition * Comment Condition	.04	2	.19	.04	.96	.00
Error	160.60	319	.50			
Total	5307.79	328				
Corrected Total	291.58	327				

a. R Squares = .45 (Adjusted R Squared = .44)

Figure 8 ***Estimated Marginal Means of Source Credibility for the Travel Post***

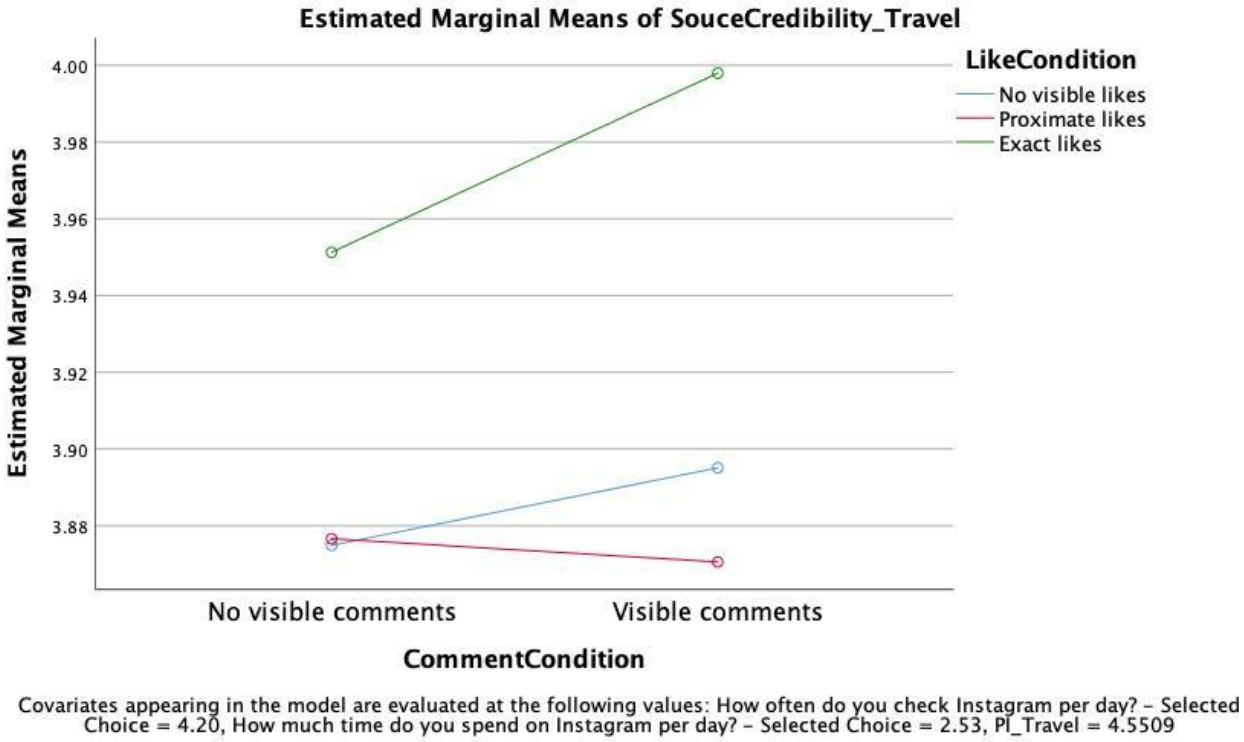


Table 25 ANCOVA Results for the Food Post

Between-Subjects Factors

		Value Label	N
Like Condition	.00	No Visible Likes	110
	1.00	Approximate Likes	110
	2.00	Exact Likes	108
Comment Condition	.00	Non-visible comments	164
	1.00	Visible Comments	164

Descriptive Statics

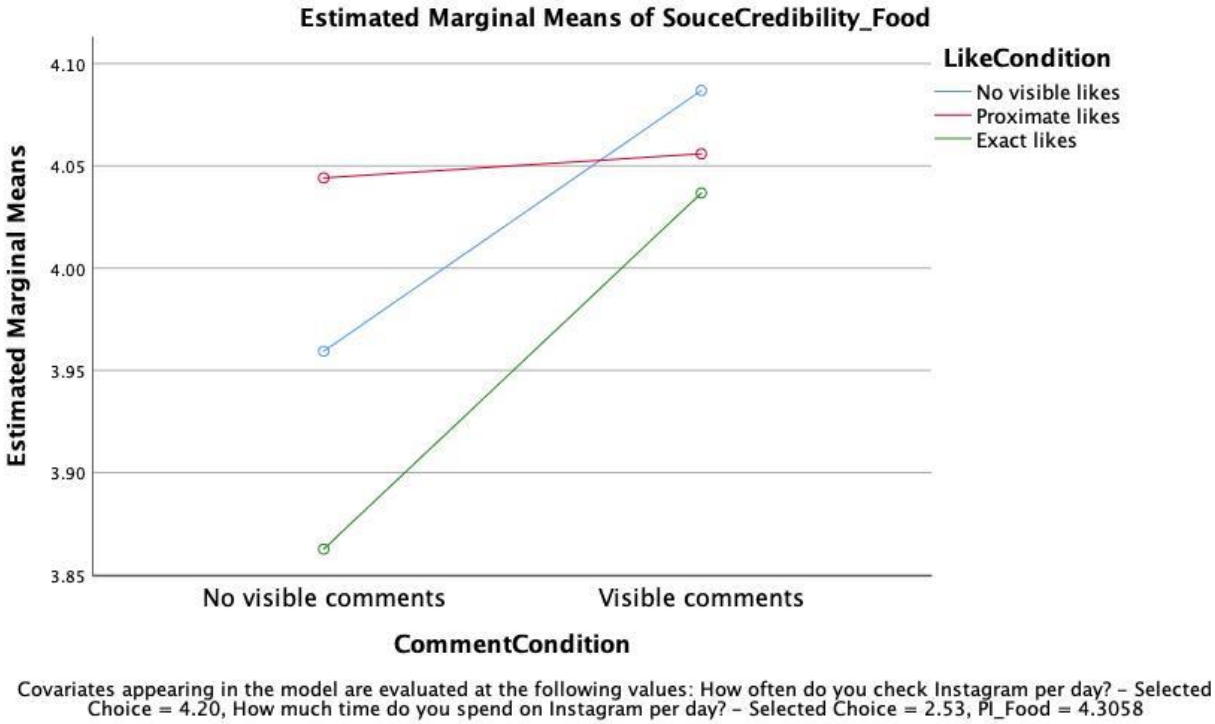
Dependent Variable: Source Credibility for Food Influencer				
Comment Condition	**Like Condition**	**Mean**	**Std. Deviation**	**N**
Non-visible comments	Non-Visible Likes	3.84	1.18	55
	Approximate likes	4.13	1.05	55
	Exact Likes	3.92	.97	54
	Total	3.97	1.07	164
Visible Comments	Non-Visible Likes	4.08	.90	55
	Approximate likes	3.96	.97	55
	Exact Likes	4.11	1.04	54
	Total	4.05	.97	164
Total	Non-Visible Likes	3.96	1.05	110
	Approximate likes	4.05	1.01	110
	Exact Likes	4.02	1.00	108
	Total	4.01	1.02	328

Test of Between-Subjects Effects

Dependent Variable: Source Credibility for Food Influencer						
Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Square
Corrected Model	119.92[a]	8	14.99	21.78	.00	.35
Intercept	40.17	1	40.17	58.38	.00	.16
Frequency	.20	1	.20	.30	.59	.00
Time	.45	1	.45	.66	.42	.00
Personal Involvement Travel	116.16	1	116.16	168.83	.00	.35
Comment Condition	.88	1	.88	1.28	.26	.00
Like Condition	.58	2	.29	.42	.66	.00
Like Condition * Comment Condition	.38	2	.19	.28	.76	.00
Error	219.48	319	.688			
Total	5608.22	328				
Corrected Total	339.40	327				

a. R Squared = .35 (Adjusted R Square = .34)

Figure 9 Estimate Marginal Means of Source Credibilty for the Food Post



The first hypotheses (H1a-b) predicted that a visible like count would elicit higher source credibility perceptions than a non-visible like count. The ANCOVA results showed that the main effect of like count display on source credibility was not statically significant for either the travel influencer's post (F (2, 319) = .66, p = .52) or the food influencer's post (F (2, 319) = .42, p = .66). These results suggest that the visual display of like counts does not significantly influence source credibility evaluations of influencers found on the Explore page. Thus, H1a and H1b were not supported.

The second hypothesis (H2) predicted that a visible comment count would elicit higher source credibility perceptions than non-visible comment count. ANCOVA results showed that the main effect of comment display on source credibility was not statistically significant for either the travel influencer's post (F (1, 319) = .07, p = .80) or the food

influencer's post (F (1, 319) = 1.28, p = .26). These results suggest that the visual display of a comment count does not significantly influence source credibility evaluations of influencers found on the Explore page. Therefore, H2 was not supported.

The third hypotheses pertains to the interplay of like counts and comment counts on source credibility perceptions. H3a and H3b predicted that posts with two forms of visible user-generated engagement cues will elicit higher source credibility perceptions than posts that feature one or less visible user-generated engagement cues. ANCOVA results showed that there were no significant interaction effects on source credibility for the travel influencer's post (F (1, 319) = .04, p = .96) or the food influencer's post (F (1, 319) = .28, p = .76) when controlling for personal involvement and Instagram use. These results suggest that the interaction of a visible like count display and visible comment count display have no significant effect on source credibility evaluations of influencers found on the Explore page. H3a and H3b were not supported. See table 14 for a visual representation of the hypothesis testing results.

Table 26 Hypotheses Results

	Results
H1a	Not Supported
H1b	Not Supported
H2	Not Supported
H3a	Not Supported
H3a	Not Supported

CHAPTER 5. DISCUSSION

5.1 Key Findings and Theoretical Implications

The objective of this research was to explore whether the visibility of user-generated engagement cues in the forms of a like count and comment count affects the source credibility perceptions of Instagram influencers discovered on the Explore page. With Instagram's (2021) recent announcement that users can choose whether or not their account shows the visible like count, it was imperative to see if this change would affect how Instagram users form judgments about influencers. Based on the heuristic systematic model, MAIN model and warranting principle, the study hypothesized that user-generated engagement would be utilized as an agency cue in order to make a quick decision regarding the quality and credibility of an influencer's post (Sundar, 2008). However, contrary to the predictions, study results reveal that the varying levels of visibility for the like count display – whether exact, approximate, or hidden – did not significantly differ in source credibility perceptions of the travel or food influencers. Similarly, study results found that the visibility of comment count display – whether visible or non-visible – did not have a significant effect on source credibility perceptions of travel or food influencers.

Additionally, this study hypothesized that the presence of multiple cues would increase the warranting value of the cue (Walter et al., 2009). The results showed that the presence of two user-generated engagement cues did not differ from the single user-generated engagement cues or non-visible cues on source credibility perceptions. While past research has found that user-generated engagement functions as a signal that

information is reliable and the volume of user-generated information leads to higher levels of warranting value and perceived information credibility (Flanagin & Metzger, 2013), the present study did not confirm previous findings. Instead, it provided novel empirical evidence for the non-significant results of warranting cues on credibility evaluations.

The researcher provides four possible explanations for the non-significant results in the following section. First, the present study manipulated the types of like count displays with either abstract information (e.g. “thousands of others”), concrete information (e.g., “4057 others”), or no information. The results indicated that the different wordings of the like count display might generate a similar level of warranting values, contributing to the current literature. However, it is worth noting that this study did not manipulate the volume of likes (e.g., “liked by ten people” vs. “liked by thousands of people”), which may generate varying levels of warranting values. Future studies could consider investigating the effect of displaying different volumes of likes on source credibility evaluations.

Second, this study displays the comments solely as an aggregated quantitative number (i.e., 164 comments”), rather than displaying the descriptive statements of personal opinions. Previous research that has found a significant effect of user-generated engagement on credibility has used qualitative displays of social support (Flanagan & Metzger, 2013; Peter et al., 2014; Xu et al., 2016). The results indicate that displaying the aggregated number of comments may not communicate direct individual recommendations as much as the qualitative comments which convey the valence of users’ comments. Additionally, the results may indicate that people may rely more on the

content of comments rather than the number of comments when forming credibility evaluations. Therefore, future research could consider examining the effect of displaying comments with the valiance information on source credibility evaluation.

Additionally, the non-significant results could be a result of the failure of the manipulation of the exact-like display. Particularly, participants had a lot of trouble distinguishing between the approximate and exact like display. Both the approximate like display (i.e., thousands of others) and the exact like display (i.e., 4057) feature a number, which may have led to the confusion as a result of perceived similarly of the two like count display conditions. It could also be possible that some participants have been used to seeing the non-visible and approximate like display since Instagram rolled out the test. Since the affordance of the like count display was not noticed by the message receivers, the cue may not have served as a trigger for heuristic processing and the participants may not have accessed the judgement rule. Future studies should include follow-up, open-ended questions that examine how participants perceive and understand the display of likes on an Instagram post, which would give more insight on if heuristic processing occurred and, if so, what cues were relied on.

The last reason for non-significant results may be because the participants did not rely on heuristic processing or the specific bandwagon cues of user-generated engagement. The results revealed the importance of personal involvement in source credibility evaluations by showing that personal involvement was a significant covariate across both message types. As past heuristic-systematic processing model literature notes, the route of persuasion someone enters during message processing is based on their level of involvement (Sengupta et al., 1997). Although this study measured and

statically controlled for personal involvement in the analysis, it did not methodologically control for personal involvement.

5.1.1 Practical implications

Instagram's test of the removal of visible likes was in an effort to reduce the pressures of being perfect on social media (Instagram, 2020). This change in visibility worried influencers whose livelihood is based on remaining visible in individual's feeds (Yurieff, 2019). This study shows that removing visible like counts on Instagram will not affect how people perceive influencers' source credibility. This is a positive outcome, as Influencers can choose to hide like counts in an attempt to improve users' mental wellness, without negatively impacting their credibility. While this study particularly pertained to Instagram, there are similarities between Instagram and other social media platforms. Therefore, this study can contribute to the overarching industry standards for social media and can be used to recommend the testing of visible like counts on other social media platforms Future research could look at the effect of varying levels of like and comment visibility on someone's mental health.

Additionally, the results that personal involvement has a positive impact on making credibility judgment is a positive finding for influencers on Instagram and other social media sites that categorize media based on interests. Rather than basing judgments on other's social endorsements, this study found the users are making judgments based on their involvement with the content that they are seeing. This finding translates into content strategy. Influencers should ensure that their content fits their defined niche. Particularly on the Explore page, influencers should strive to be featured on specific Explore page channels that best fit their niche. By working with Instagram's algorithm

that priorities relevancy, influencers can thrive and receive high source credibility evaluations from those who have a higher level of personal involvement with the area of interest.

As for comments, the results show that the visibility of a comment display has no effect on source credibility perceptions of an Influencer discovered on the Explore page. Therefore, Instagram's Explore page does not need to be modified to show an aggregated comment display. The Explore page currently only features the caption of a post. As mentioned previously, future studies could evaluate if the addition of qualitative displays, rather than quantitative displays, of comments effect source credibility perceptions.

5.2 Limitations and Future Research

The nature of an experiment leads to lower levels of external validity. As this study was an online experiment, the artificial environment could have affected source credibility evaluations. On the platform, users can look through an influencer's profile to form source credibility evaluations; in this study, participants formed an evaluation on a static image they themselves did not click. Participants were shown a still picture of an Explore page, rather than being able to scroll and interact with the page. Additionally, participants did not get to choose the post of interest or the Explore page category. Rather, the post and category were prechosen for them. Similarly, the artificial environment could have led participants to pay more attention to the posts in the experiment than they usually would have in their typical Instagram use. Future studies could enhance external validity by recording how participants act on the app rather than in an artificial environment. Since participants were engaging in an online task rather than scrolling through the app for pleasure and entertainment, the participants may have

systematically processed the posts rather than heuristically. In this case, it makes sense that the heuristic cues of user-generated engagement were not relied on to make credibility judgements. Future studies could consider priming participants to use heuristics processing when exposed to the stimuli or examine how different levels of involvement would moderate the effect.

This study particularly focused on the visibility of user-generated engagement in forming source credibility evaluations. Since the visibility of user generated engagement did not affect source credibility evaluations, it would be beneficial to continue research on other factors that may contribute to source credibility perceptions. For example, the Instagram Verification Checkmark would be a valuable avenue of study, as it is a third-party cue that can communicate warranting value (DeAndrea, 2014). Additionally, future studies could look at other types of social endorsements on Instagram, such as the presence of a friends' name in the like display. The degree of the user's connection to the friend who appears in the like displayed may play an important role in forming source credibility perceptions.

This study only looked at the metrics of likes and comments and examined source credibility as the outcome. However, saves are another way that users can interact with a post. To save an image or video, users must tap the bookmark icon underneath the post (Eadicicco, 2016). The save feature originally started as a way for people to archive posts for later viewing in one convenient place. Now, "saves" are considered an increasingly important metric as the more saves a post receives, the larger the number of users the post will be shown to (Canning, 2019). Although the number of saves is not visible in the same way as comments and likes, it is a metric that will become increasingly important in

assessing an influencer's influence from an advertising standpoint. Future studies could test and see whether likes and comments influence people making the saves on Instagram posts, or forming other attitudes or behavioral intentions.

Additionally, this study used a static image as the Instagram post. Future studies can expand to other formats that are increasing in popularity, such as Reels. Reels are short, 15-second video clips that users create (Instagram Press, 2020b). For private accounts, Reels can be shared in a user's feed to their friends. Users with a public account can also share Reels in the Explore and Reels tab (Instagram Press, 2020b). Reels can be liked, commented on, or shared.

The present study investigated the effect of user-generated engagement on posts that did not feature a product. Future research could focus especially on investigating if user-generated engagement is more heavily relied on when there is a purchase decision in play, rather than a low-involvement non-branded post. Based on HSM, scrolling through Instagram and evaluating an influencer tends to be a low involvement activity while making a purchase decision may rely more on content than cues due to their heightened purchase involvement. Future research could test the effect of varying levels of likes and comments among varying message types.

Lastly, this study was interested in examining Generation Z and Millennial's behavior in regards to the formation of source credibility evaluations of Influencers on the Explore page of Instagram, as 60% of Instagram users in the United States are under the age of 34 (Haenlein et al., 2020). These two generations are known for avidly following and genuinely trusting social media influencers (ANA, 2018). Due to the sample of this study, only individuals falling into Generation Z were studied. Therefore, a

large segment of Instagram's top users were not included in this study. Future studies could evaluate if Millennials rely on user-generated engagement cues differently than Generation Z when forming source credibility perceptions of influencers who were 15discovered on the Explore page. Similarly, the social media platform of TikTok has seen a rise in use among Generation Z (Beganovich, 2020). TikTok, like Instagram, features a visible like count and is a popular platform for influencer marketing. Future studies could evaluate if there are platform (i.e., Instagram and TikTok) differences in how Generation Z and Millennial users rely on user-generated engagement cues when evaluating the source credibility of influencers.

APPENDICES

APPENDIX A. IRB APPROVAL LETTER

University of Kentucky | Office of Research Integrity
IRB, RDRC

Modification Review

Approval Ends:	IRB Number:
11/29/2026	63269

TO:	Madison Wallace Integrated Strategic Communications PI phone #: 5026823611 PI email: MadisonLWallace@uky.edu
FROM:	Chairperson/Vice Chairperson Nonmedical Institutional Review Board (IRB)
SUBJECT:	Approval of Modification Request
DATE:	4/30/2021

On 4/30/2021, the Nonmedical Institutional Review Board approved your request for modifications in your protocol entitled:

The Persuasive Power of Instagram: Examining How User-generated Warranting Cues Affect Consumer's Perception of Influencer Credibility

In addition to IRB approval, you must also meet the requirements of the VPR Resumption of Research Phased Plan (i.e., waiver for Phase 1, training & individualized plan submission for Phases 2-4) before resuming/beginning your human subjects research. If your modification request necessitated a change in your approved informed consent/assent form(s), the new IRB approved consent/assent form(s) to be used when enrolling subjects can be found on the approved application's landing page in E-IRB. [Note, subjects can only be enrolled using consent/assent forms which have a valid "IRB Approval" stamp unless special waiver has been obtained from the IRB.]

Note that at Continuation Review, you will be asked to submit a brief summary of any modifications approved by the IRB since initial review or the last continuation review, which may impact subject safety or welfare. Please take this approved modification into consideration when preparing your summary.

For information describing investigator responsibilities after obtaining IRB approval, download and read the document "PI Guidance to Responsibilities, Qualifications, Records and Documentation of Human Subjects Research" available in the online Office of Research Integrity's IRB Survival Handbook. Additional information regarding IRB review, federal regulations, and institutional policies may be found through ORI's web site. If you have questions, need additional information, or would like a paper copy of the above mentioned document, contact the Office of Research Integrity at 859-257-9428.

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APPENDIX B. ONLINE SURVEY

Consent Form

KEY INFORMATION FOR INFLUENCER CREDIBILITY PILOT

Consent to Participate in a Research Study

KEY INFORMATION FOR INFLUENCER CREDIBILITY PILOT
We are asking you to choose whether or not to volunteer for a research study about people's Instagram use and perceptions of influencers. We are asking you because you are between the age of 18 and 26 and use Instagram. This page is to give you key information to help you decide whether to participate. We have included detailed information after this page. Ask the research team questions. If you have questions later, the contact information for the research investigator in charge of the study is below.

WHAT IS THE STUDY ABOUT AND HOW LONG WILL IT LAST?
By doing this study, we hope to learn how people evaluate influencers on Instagram. In this study, you will be asked to view a series of Instagram posts on a computer screen and be asked to fill out a brief survey about your opinions and Instagram use. This research is completely virtual and will take approximately 30 minutes to complete, including the informed consent process. You may complete the virtual experiment at a time and location that is convenient to you. All portions of this experiment will be completed virtually through a Qualtrics survey. Survey data will be recorded. While no identifiable data will be collected, we will keep all research records private to the extent outlined by the law. Completion of this experiment will account for 1 SONA credit. If you do not wish to participate, there are alternatives to earning this credit.

WHAT ARE KEY REASONS YOU MIGHT CHOOSE TO VOLUNTEER FOR THIS STUDY?
Although you may not gain personal benefit from taking part in this research study, your response may help us understand more about the perceptions of influencers on Instagram. Some volunteers experience satisfaction from knowing they have contributed to research that may possibly benefit others in the future.

WHAT ARE KEY REASONS YOU MIGHT CHOOSE NOT TO VOLUNTEER FOR THIS STUDY?
There are no expected risks associated with participating in this study. However, participants may experience mild psychological discomfort while reflecting on questions.

DO YOU HAVE TO TAKE PART IN THE STUDY?
If you decide to take part in the study, it should be because you really want to volunteer. You will not lose any services, benefits, or rights you would normally have if you choose not to volunteer. As a student, if you decide not to take part in this study, your choice will have no effect on your academic status or class grade(s).

WHAT IF YOU HAVE QUESTIONS, SUGGESTIONS OR CONCERNS?
If you have questions, suggestions, or concerns regarding this study or you want to withdraw from the study contact Madison Wallace of the University of Kentucky, Department of Communication and Information at mlwa272@uky.edu or (502) 682-3611.

If you have any concerns or questions about your rights as a volunteer in this research, contact staff in the University of Kentucky (UK) Office of Research Integrity (ORI) between the business hours of 8am and 5pm EST, Monday-Friday at 859-257-9428 or toll-free at 1-866-400-9428.

DETAILED CONSENT:
ARE THERE REASONS WHY YOU WOULD NOT QUALIFY FOR THIS STUDY?
Study participants must be between the ages of 18 and 26, must use Instagram, and must be willing to participate in the questionnaire in English. Individuals who do not meet these criteria will not be eligible for this study.

WHERE WILL THE STUDY TAKE PLACE AND WHAT IS THE TOTAL AMOUNT OF TIME INVOLVED?
The research procedures will be conducted virtually through a Qualtrics survey at a time and location convenient to you. The total amount of time you will be asked to volunteer for this study is 30 minutes over a one-day period.

WHAT WILL YOU BE ASKED TO DO?
You will be invited to participate in a study at a time and location that is convenient for you. You will be asked to complete a brief survey regarding demographic characteristics, Instagram usage, and your perceptions about visuals presented to you. You are free to skip any questions that you do not wish to answer or discuss. At the conclusion of the session, you will receive 1 SONA credit for your effort.

WHAT ARE THE POSSIBLE RISKS AND DISCOMFORTS?
Potential risks, however low and unlikely, include the possibility of distress related to mild psychological discomfort while reflecting on questions. In addition to the risk described in this consent, you may experience a previously unknown risk or side effect.

WILL YOU BENEFIT FROM TAKING PART IN THIS STUDY?
We do not know if you will get any benefit from taking part in this study. However, some people may benefit from learning more about their social media use and perception of influencers. Additionally, if you take part in this study, the information learned may help others.

IF YOU DON'T WANT TO TAKE PART IN THE STUDY, ARE THERE OTHER CHOICES?

If you do not want to take part in the study, there are other choices such as participation in other studies unrelated to this one or completion of alternative non-research course activities to earn SONA credit.

WHAT WILL IT COST YOU TO PARTICIPATE?
There are no costs associated with taking part in this study.

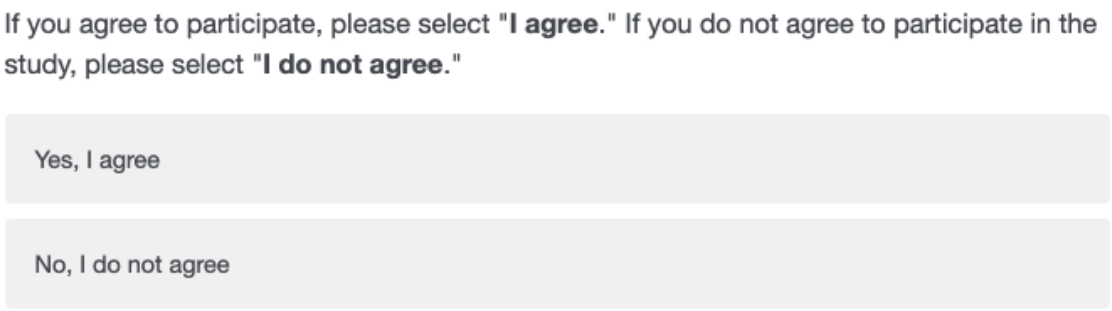
WHO WILL SEE THE INFORMATION THAT YOU GIVE?
Your response to the survey is anonymous which means no names, IP addresses, email addresses, or any other identifiable information will be collected with the survey responses. We will not know which responses are yours if you choose to participate. We will make every effort to safeguard your data, but as with anything online, we cannot guarantee the security of data obtained via the Internet. Third-party applications used in this study may have Terms of Service and Privacy policies outside of the control of the University of Kentucky.

CAN YOU CHOOSE TO WITHDRAW FROM THE STUDY EARLY?
You can choose to leave the study at any time. You will not be treated differently if you decide to stop taking part in the study.
If you choose to leave the study early, data collected until that point will remain in the study database and may not be removed.

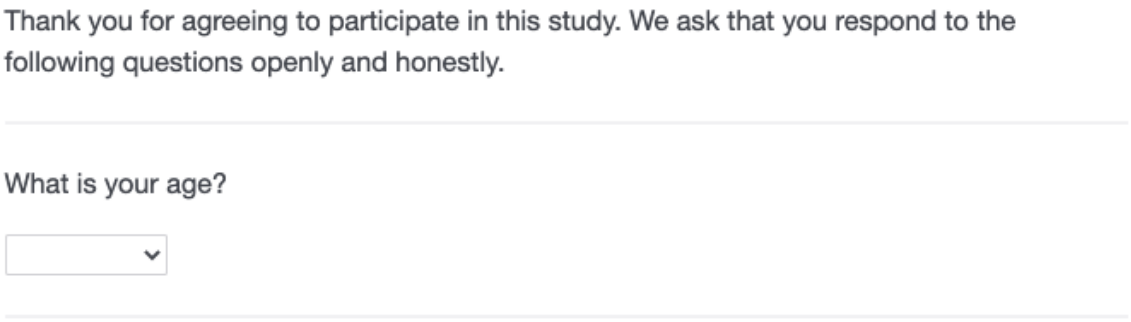
ARE YOU PARTICIPATING, OR CAN YOU PARTICIPATE, IN ANOTHER RESEARCH STUDY AT THE SAME TIME AS PARTICIPATING IN THIS ONE?
You may take part in this study if you are currently involved in another research study.

WILL YOU RECEIVE ANY REWARDS FOR TAKING PART IN THIS STUDY?
You will receive SONA credit for taking part in the study.

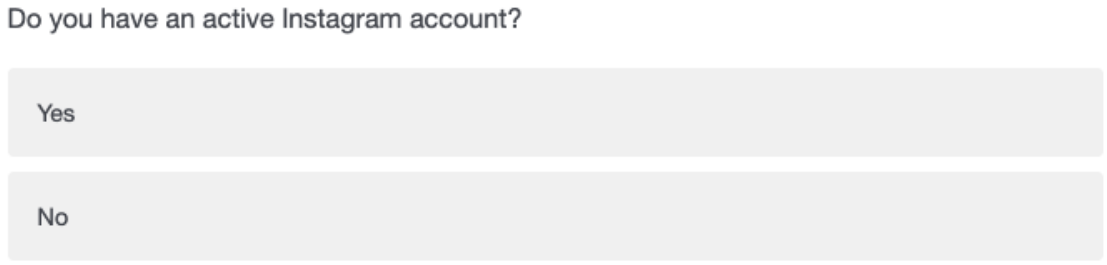
WHAT ELSE DO YOU NEED TO KNOW?
If you volunteer to take part in this study, you will be one of about 150 people to do so. The Principal Investigator is a master's student at the University of Kentucky. She is being guided in this research by Dr. Jiang. There may be other people on the research team assisting at different times during the study. You can contact Dr. Jiang at Mengtian.Jiang@uky.edu.



(Those who selected "I agree" then progressed on to the screener questions. Those we selected "I disagree" progressed on to an end of survey message.)



(*Participants selected from a drop down box with the following categories: 17, 18, 19 , 20, 21, 22, 23, 24, 25, 26, 27 or older. If an individual selected "17" or "27 or older," they were presented an end of survey message since they did not meet the section criteria).*



(If an individual selected "No," they were presented an end of survey message since they did not meet the selection criteria of having an active Instagram account. Those who selected yes progressed on.)

(Participants were then randomly presented with one of two scenarios: the travel scenario or the food scenario.)

This study requires that you imagine yourself in the following scenario:
Imagine that you have just picked up your device and decided to open Instagram. You decided to click on the magnifying glass icon and are taken to the Explore page. On the Explore page, you can find photos and videos that you might like from accounts you don't follow yet. At the top of the screen, you see a list of curated topics and **decide to click on "Travel" ("Food")**. The image below shows what your screen would look like. In this scenario, **you decide to click on the top left photo to get a better view of the post**.

Image for travel scenario:

Image for food scenario:

(Participants would then be randomly presented with one of six conditions based on the theme that they were randomly selected for and would read the following instructions.)

Now that you've clicked on the image, you have a better view and can further explore the post. For this scenario, **please imagine that you have a friend named Adrian Smith (Bailey Williams).** You may know this individual better by their username **@arsmith (@itsbaileyw).**
As you read the following Instagram post, click up to three parts of the post that stand out to you (e.g., the first three elements that you looked at). A red dot will appear where you click.

Condition 1T: Travel post with non-visible likes and no visible comments

Condition 2T: Travel post with approximate likes and no visible comments

Condition 3T: Travel post with exact likes and non-visible comments

Condition 4T: Travel post with non-visible likes and visible comments

Condition 5T: Travel post with approximate likes and visible comments

Condition 6T: Travel post with exact likes and visible comments

Condition 1F: Food post with non-visible likes and no visible comments

Condition 2F: Food post with approximate likes and no visible comments

Condition 3F: Food post with exact likes and non-visible comments

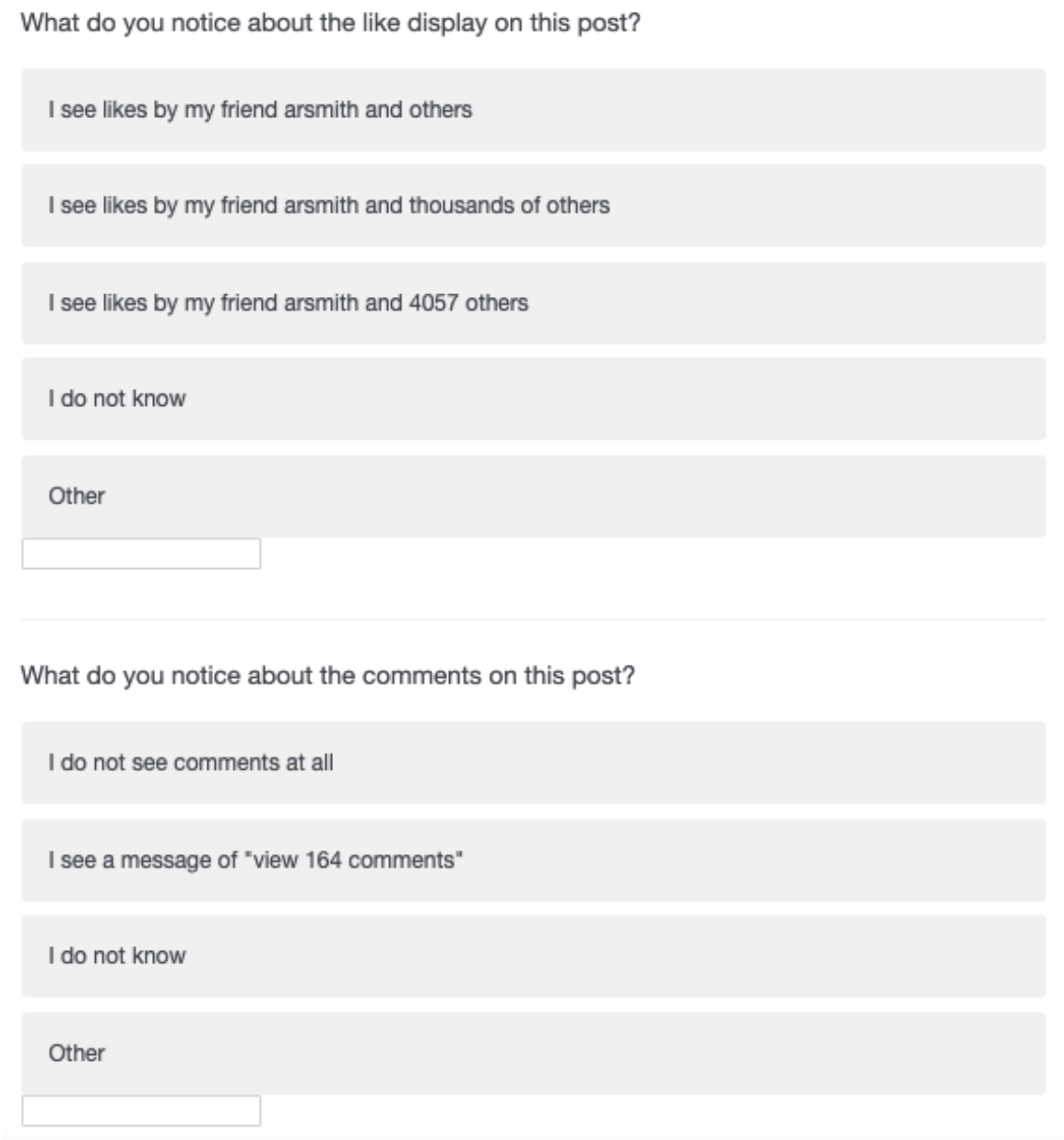
Condition 4F: Food post with non-visible likes and visible comments

Condition 5F: Food post with approximate likes and visible comments

Condition 6T: Food post with exact likes and visible comments

(Participants would then respond to two questions regarding the like and comment display of the post. The question wording was changed to reflect the theme of the post.)

Like and comment questions for the travel themed post:



Like and comment questions for the food themed post:

What do you notice about the like display on this post?

- I see likes by my friend itsbaileyw and others
- I see likes by my friend itsbaileyw and thousands of others
- I see likes by my friend itsbaileyw and 4057 of others
- I do not know
- Other

What do you notice about the comments on this post?

- I do not see comments at all
- I see a message of "view 164 comments"
- I do not know
- Other

Please indicate your perception of the source by selecting the option that most closely aligns with your reaction to the Instagram Influencer.

Dependable	○ ○ ○ ○ ○ ○ ○	Undependable
Unskilled	○ ○ ○ ○ ○ ○ ○	Skilled
Qualified	○ ○ ○ ○ ○ ○ ○	Unqualified
Dishonest	○ ○ ○ ○ ○ ○ ○	Honest
Unknowledgeable	○ ○ ○ ○ ○ ○ ○	Knowledgeable
Insincere	○ ○ ○ ○ ○ ○ ○	Sincere
Experienced	○ ○ ○ ○ ○ ○ ○	Inexperienced
Trustworthy	○ ○ ○ ○ ○ ○ ○	Untrustworthy
Reliable	○ ○ ○ ○ ○ ○ ○	Unreliable
Not an expert	○ ○ ○ ○ ○ ○ ○	Expert

Attention check question for the travel scenario:

Paying attention and reading the instructions carefully is critical. If you are paying attention, please choose "Yellow" below.

- Red
- Blue
- Yellow
- Green

Attention check question for the food scenario:

Paying attention and reading the instructions carefully is critical. If you are paying attention, please choose "Red" below.

- Red
- Blue
- Yellow
- Green

After viewing the post, please indicate your feelings regarding the post by selecting the option that most closely aligns with your thoughts.

Means nothing to me	○ ○ ○ ○ ○ ○ ○	Means a lot to me
Fascinating	○ ○ ○ ○ ○ ○ ○	Mundane
Boring	○ ○ ○ ○ ○ ○ ○	Interesting
Involving	○ ○ ○ ○ ○ ○ ○	Uninvolving
Important	○ ○ ○ ○ ○ ○ ○	Unimportant
Worthless	○ ○ ○ ○ ○ ○ ○	Valuable
Not needed	○ ○ ○ ○ ○ ○ ○	Needed
Exciting	○ ○ ○ ○ ○ ○ ○	Unexciting
Relevant	○ ○ ○ ○ ○ ○ ○	Irrelevant
Appealing	○ ○ ○ ○ ○ ○ ○	Unappealing

(Participants would then be directed to the other scenario that they did not initially respond to and repeat everything from the scenario instructions to this point. After completing the second scenario, participants responded to demographic questions.)

Now, we would like you to answer a few questions about yourself.

What is your gender?

- Male
- Female
- Other (please specify)
- Prefer not to answer

What is your racial/ethnic background?

- Asian
- American Indian or Alaska Native
- Black or African American
- Hispanic/Latino(a)
- Native Hawaiian or Pacific Islander
- White
- Mixed Race
- Other (please specify)
- Prefer not to answer

What is your classification level?

- Freshman
- Sophomore
- Junior
- Senior

How often do you check Instagram per day?

- On every notification beep
- 1-2 times per day
- 3-4 times per day
- 5-6 times per day
- 7-8 times per day
- 9+ times per day
- Other (please specify)

How much time do you spend on Instagram per day?

- Less than 15 minutes
- 30 minutes to 1 hour
- 1-2 hours
- 3-4 hours
- 5-6 hours
- 7-8 hours
- 9+ hours
- Other (please specify)

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